Agricultural and Forest Meteorology 253–254 (2018) 94–113

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Multi-model projections of future climate and climate change impacts uncertainty assessment for cotton production in Pakistan

Muhammad Habib ur Rahman[a,b,**], Ashfaq Ahmad[c], Xuechun Wang[d], Aftab Wajid[c], Wajid Nasim[e,***], Manzoor Hussain[f], Burhan Ahmad[g], Ishfaq Ahmad[c], Zulfiqar Ali[h], Wajid Ishaque[f], Muhammad Awais[i], Vakhtang Shelia[b,j], Shakeel Ahmad[k], Shah Fahd[l,m,*], Mukhtar Alam[m], Hidayat Ullah[m], Gerrit Hoogenboom[b,j]

[a] Department of Agronomy, Muhammad Nawaz Shareef University of Agriculture, Multan, Punjab, Pakistan
[b] AgWeather Net, Washington State University, Prosser, WA, USA
[c] Agro-Climatology Lab., Department of Agronomy, University of Agriculture, Faisalabad, Pakistan
[d] School of Life Science and Technology, South West University of Science and Technology, No.59, Qinglong Road, Mianyang, Sichuan, 621010, China
[e] Department of Environmental Sciences, COMSATS Institute of Information Technology (CIIT), Vehari, Pakistan
[f] Nuclear Institute for Agriculture and Biology (NIAB), Faisalabad, Punjab, Pakistan
[g] Pakistan Meteorological Department (PMD), Islamabad, Pakistan
[h] Department of Plant Breeding and Genetics, Muhammad Nawaz Shareef University of Agriculture, Multan, Punjab, Pakistan
[i] Department of Agronomy, University College of Agriculture and Environmental Sciences, The Islamia University of Bahwalpur, Pakistan
[j] Agricultural and Biological Engineering Department, Institute for Sustainable Food Systems (ISFS), University of Florida, USA
[k] Department of Agronomy, Faculty of Agricultural Sciences and Technology, (FAST), Bahauddin Zakariya University, Multan, 60800, Pakistan
[l] College of Plant Science and Technology, Huazhong Agricultural University, Wuhan, Hubei, China
[m] Department of Agriculture, University of Swabi, Khyber Pakhtunkhwa, Pakistan

ARTICLE INFO

Keywords:
GCMs
RCPs
CTWN analysis
Sustainable cotton production
Adaptation options
Multi-model ensemble

ABSTRACT

Future climate projections and impact assessments are critical in evaluating the potential impacts of climate change and climate variability on crop production. Climate change impact assessment in combination with crop, climate models under different climate change scenarios is uncertain and it is challenging to select an appropriate climate scenario. This study quantifies the uncertainty associated with projected climate change impacts on cotton yield in Punjab, Pakistan using 29 general circulation models (GCMs) under high and moderate representative concentration pathway (RCP) scenarios (4.5 and 8.5) at near-term (2010–2039) and mid-century (2040–2069) time spans. Cropping System Model (CSM) CROPGRO-Cotton (DSSAT *v* 4.6) was calibrated and evaluated with field experiment data collected under arid/semi-arid climatic conditions. Enormous variation was observed in GCMs climatic variables, which were therefore classified into different categories. According to mean ensemble of 29 GCMs, there is a projected increase in seasonal average temperature 1.52 °C and 2.60 °C in RCP 4.5 and 1.57 °C and 3.37 °C in RCP 8.5 scenario as compared to the seasonal baseline (31.48 °C) in near-term (2010–2039) and mid-century (2040–2069), respectively. Maximum consensus by GCMs revealed the increase in temperature of 1.2–1.8 °C and 2.2 to 3.1 °C in RCP 4.5 scenario while 1.4–2.2 °C and 3.0–3.9 °C increase is expected under RCP 8.5 for near term and mid-century time periods, respectively. Similarly, rainfall changes are expected −8% to 15% and −5 to 17% in RCP 4.5 scenario while −8 to 22% and −2 to 20% change is expected under RCP 8.5 scenario in near term and mid-century time periods, respectively. Seed cotton yield (SCY) are projected to decrease by 8% on average by 2039 and 20% by 2069under the RCP 4.5 scenario relative to the baseline (1980–2010). Mean seed cotton yield is projected to decrease by 12% and 30% on average under the RCP 8.5 scenario. Uncertainties were observed in GCMs projections and RCPs due to variations in climatic variables projections. GCMs, GFDL-ESM2M (45% and 35%), GFDL-ESM2G (28% and 43%) and MIROC-ESM (39% and 70%) predicted the higher mean SCY reduction ensemble of cultivars than others under emission scenario of 4.5 in near term and mid-century, respectively. Lower SCY reduction was revealed in CCSM4, HADGEM2-CC, HADGEM2-ES, INMCM4 and CNRM-CM5 due to mild behavior of climatic variables especially temperature under RCP 4.5 in the near-term and mid-century. High reduction in mean SCY (16%–19%) is

* Corresponding author at: College of Plant Science and Technology, Huazhong Agricultural University, Wuhan, Hubei, China.
** Corresponding author at: Department of Agronomy, Muhammad Nawaz Shareef University of Agriculture, Multan, Punjab, Pakistan.
*** Corresponding author.
E-mail addresses: habib.rahman@mnsuam.edu.pk (M.H.u. Rahman), wajidnaseem2001@gmail.com (W. Nasim), shah_fahad80@yahoo.com, shah.fahad@mail.hzau.edu.cn (S. Fahd).

https://doi.org/10.1016/j.agrformet.2018.02.008
Received 3 January 2017; Received in revised form 12 September 2017; Accepted 12 February 2018
Available online 17 February 2018
0168-1923/

expected in CMCC-CMS, IPSL-CM5B-LR, GISS-E2-H, GFDL-ESM2M and GFDL-ESM2G under the RCP 8.5 scenario. However, under the same scenario, mean SCY increases by 1% in HADGEM2-ES and by 4% in HADGEM2-CC relative to the baseline yield (4147 kg ha^{-1}). GFDL-ESM2M and GFDL-ESM2G are hot and dry while HADGEM2-ES and HADGEM2-CC are hot but wet, resulting in less cotton yield loss. MIROC-ESM and GFDL-ESM2G projected a severe reduction in mean SCY (70% and 69%) due to a steep increase in maximum and minimum temperature (6.97 °C and 4.38 °C, 4.91 °C and 3.70 °C), respectively and sever reduction in rainfall by mid-century and may call worse case scenarios. Climate models like, CCSM4, HadGEM2-CC, HadGEM2-ES, INMCM4, CanESM2, CNRM-CM5, ACCESS1-0, BNU-ESM and MIROC5 are found less uncertain and showed stable behavior. Therefore, these models can be used for climate change impact assessment for other crops in the region. Adaptation management options like five weeks early sowing than current (10-May), increasing nitrogen fertilization (30%), higher planting density (18% for spreading and 30% for erect type cultivars) and 17% enhanced genetic potential of cultivars would compensate the negative impacts of climate change on cotton crop. This study provide valuable understandings and direction for cotton management options under climate change scenarios. This multi-model and multi-scenario analysis provides a first overview of projected changes in temperature and precipitation, cotton yield and potential management options under changing climate scenarios in arid to semi-arid climatic conditions of Punjab-Pakistan.

1. Introduction

Climate change is expected to increase the vulnerability of agricultural systems (Rosenzweig et al., 2014) by increasing temperature, changes in rainfall patterns, and increased frequency of extreme weatehr events in most parts of the world (IPCC, 2014) and especially in Pakistan (Ahmad et al., 2015; Nasim et al., 2016). Projected changes are expected to have a negative impact on crops in Paksitan, especially in arid to semi-arid regions (IPCC, 2013; Ahmad et al., 2015; Rasul et al., 2016; Abbas et al., 2017). Cotton is the most important cash crop in Pakistan, providing feed, fiber and oil. It holds a lion's share in the foreign exchange (55%) and production accounts for 1.5% in GDP and 7.1% in value added agriculture (GOP, 2015). Increases in temperature and changes in precipation may have negative impact on cotton growth and productivity (Bange and Milroy, 2004; Gwimbi and Mundoga, 2010; Iqbal et al., 2016). Elevated CO_2 concentration (eCO_2) positively relates to crop growth, biomass and cotton yield by promoting photosynthesis and decreasing transpiration and stomatal conductance and overall it enhances water use efficiency (Williams et al., 2015; Luo et al., 2016; Fahad et al., 2016a,b,c,d). However, more recent studies have shown that interactive effects of CO_2, projected increase in temperature and variability in precipitation in future climate scenarios could potentially offset the positive effect of CO_2 induced by doubling its concentration (Paz et al., 2012; Hatfield and Prueger, 2015; Nasim et al., 2016c). Physiological and metabolic processes occurring in cotton have thermal range spanning 23–32 °C, which is considered as the optimal range for growth and development (Cottee et al., 2010; Nasim et al., 2011). Optimum temperature for efficient growth is reported to be 33 °C while significant reduction in flower and boll retention has been recorded above 36 °C (Singh et al., 2007; Luo, 2011; Nasim et al., 2016b). Cotton growth and seed cotton yield are dramatically affected by temperature variations (Nasim et al., 2011; Luo et al., 2014; Nasim et al., 2016a; Rahman et al., 2017). The boll growth period shortens with high temperature, resulting in smaller boll, and ultimately a lower cotton yield (Reddy and Zhao, 2005; Nasim et al., 2012; Fahad and Bano, 2012; Fahad et al., 2013, 2014a,b, 2015a,b). Environmental stresses, mainly temperature is the main cause of yield variability over time; high temperature during the day followed by high night temperature may exacerbate these harmful effects. Unforeseen periodic incidents of heat stress are projected to happen more frequently in the region. These changes in climatic conditions could affect cotton phenology, growth and yield, and threaten sustainable cotton production in the future.

Uncertainty in climate change impact projections are related to multiple factors including climate model and greenhouse gas emission scenario selection, complexities in atmosphere modeling, downscaling methods, incomplete understanding of the processes included in climate models and uncertainties in crop models (Wilby et al., 2009; Asseng, 2013; Challinor et al., 2013; Osborne et al., 2013; Uusitalo et al., 2015; Mason-D'Croz et al., 2016; Amin et al., 2017a). Most studies rely on only a few climate models and a single greenhouse gas (GHG) emission scenario those were unable to characterize uncertainties in climate risk assessment (Meehl et al., 2007; Bassu et al., 2014; Tao et al., 2009; Rötter et al., 2011; Amin et al., 2017b). More robust climate change impact assessment are based on multi-climate model (GCMs) projections as well as multiple scenarios (Tebaldi and Knutti, 2007; Kassie et al., 2015; Araya et al., 2015). Process-based dynamic crop models can be used for climate risk assessment (Ewert et al., 2015), but must be rigorously calibrated with growth and yield attribute data (Challinor et al., 2013; Adhikari et al., 2015; Bassu et al., 2014; Uusitalo et al., 2015; Kersebaum et al., 2015; Awais et al., 2017). As a result, models predict the expected impacts of, and uncertainties associated with climate change scenarios on the growth and yield of agricultural crops (Thorp et al., 2014; Rosenzweig et al., 2013, 2014; Ruane et al., 2013). Climate change impact assessment studies offer a means of quantifying uncertainties related to climate risks, and provide decision-support for more sustainable crop production. Crop model-derived yield predictions based on multiple GCMs and emission scenarios (RCPs) provide more reliable climate change impact assessments (Asseng, 2013; Rosenzweig et al., 2013; Ruane et al., 2013). These studies can also be used to discover and assess the uncertainty in yield predictions and as well as to evaluate model performance (White et al., 2011; Challinor et al., 2013; Wajid et al., 2013; Mason-D'Croz et al., 2016). This study aims to quantify uncertainty in climate change impact assessment on cotton production by using all available climate models (GCMs), under both harsh and mild emission scenarios from 2010 to 2069, which has not yet been done in the study region. Existing studies are limited to old emission GHGs scenarios of IPCC (A2, B2, A1B, B1) and very few GCMs and are based in parts of the world (Voloudakis et al., 2015; Gwimbi and Mundoga, 2010; Adhikari et al., 2015; Yang et al., 2014; Hebbar et al., 2013; Luo et al., 2016) where climatic conditions are very different. Specifically, our goals are to 1) assess the potential impacts of future climate change and variability on cotton production derived from CSM-CROPGRO-Cotton, and 2) quantify the uncertainty in climate change impacts projections using 29 GCMs across the world under high and moderate RCPs scenarios (4.5 and 8.5) for early (2010–2039) and mid-century (2040–2069) time spans.

2. Materials and methods

2.1. Environmental conditions of site and experimental details

The study was conducted in Punjab (31°30 N, 73°26 E), which is characterized by arid/semi-arid environmental conditions. The study area experiences important diurnal fluctuations where mean daily air

temperature ranged 24 °C–46 °C and 4 °C–23 °C during the summer and winter seasons, respectively. Maximum rainfall occurs during the monsoon season (July and August) but is highly variable. Historic long term daily weather data (1974–2013) of minimum (Tmin), maximum (Tmax) and mean air temperatures, precipitation, solar radiation, humidity and wind speed were collected from field weather observatory of Pakistan Meteorological Department (PMD). The soil is classified as Aridisol, mixed, hyperthermic Ustalfic, Haplargid and Haplic Yermosol according to soil taxonomy Soil Survey Staff and FAO-UNESCO, respectively. A silty loam, the soil is brown in color, well drained and strongly calcareous in nature. Soil has very less organic carbon in different horizons (0.46–0.14) due to its oxidation promoted by high temperature. The soil is alkaline and pH increases with depth and soil is nitrogen deficient (0.05%) which decreases in subsoil. Field experiments were conducted twice during the cotton growing season of 2012 and 2013. Planting dates and popular cotton cultivars namely MNH-886, NIAB-9811 and NIAB-112 were considered as main treatments in these experiments. The experiments were laid out in randomized complete block design (RCBD) with split plot arrangement keeping three replicates. Cotton cultivars were kept in sub plots while planting times (10-March, 30-March, 21-April, 10-May, 1-June and 21 June) were randomized in main plots.

2.2. Data collection

2.2.1. Climatic data, scenarios generation and climate change impact assessment

Long term historic measured weather data (solar radiation, maximum and minimum temperature, precipitation, surface wind, dew point temperature, relative humidity, and vapor pressure) for the present climate and baseline (1980–2010) in this study, was obtained from Pakistan Meteorological Department (PMD) and used for future climate scenarios generation of 29 GCMs in combination with RCPs (Ruane et al., 2015b). Delta scenarios approach based on historical baseline daily weather data; with each day's weather variables perturbed using the changes in climate model outputs for future time periods versus those same model outputs for the historical time period (Wilby et al., 2004) have been employed using climate scenario generation tool. Delta method scripts were run in "R" to develop future climate scenarios by using scripts of delta method (AgMIP, 2013a,b; Ruane et al., 2013). Future climate scenarios under two RCPs (4.5 and 8.5) were derived from the latest 29 IPCC climate models and downscaled for use in the target region. Climate scenarios data were generated using adjusted historical climate data records; changes in precipitation, maximum temperature and minimum temperature forecasted by climatic models runs by following the relative changes in former and absolute changes in later weather attributes as reported by Ruane et al. (2013). In the creation of Coupled Model Inter-comparison Project (CMIP5) mean and variability change scenarios, we calculated monthly changes in mean maximum temperature, minimum temperature, and precipitation by comparing future 30-year climate periods to the current (1980–2010) climate period from 29 GCMs. Then we calculated monthly changes in the standard deviation of maximum temperature, the standard deviation of minimum temperature, and the number of rainy days (precipitation > 0.1 mm) by comparing future 30-year climate periods to the current climate period from the same GCM combination. It is seen that the shape parameter of the gamma distribution for wet events is generally not of sufficient quality in GCM simulations. Therefore, we imposed these monthly changes on baseline climate series using a stretched distribution approach that adjusts each event by comparing existing and desired values by distributional percentiles (Ruane et al., 2015a). In this process, we assumed that solar radiation, winds, and relative humidity daily variables from the historical daily climate records are unchanged. We also ensured that vapor pressure, dew point temperatures, and relative humidity were physically consistent at time of maximum daily temperatures. Finally, we produced mean and variability change scenarios for all CMIP5 GCMs at the best-calibrated site of the region, and then created future scenarios for the study site using the 29-GCM to drive crop model simulations. Climate projection scenarios in future for Faisalabad region were generated from all available climate models across the world (29 GCMs) for near term (2010–2039) and mid-century (2040–2069) time spans under two RCPs: RCP4.5 (has a relatively modest increase in GHGs concentration) and RCP8.5 (has a rapid increase in GHGs concentration) using the methodology developed by AgMIP (AgMIP, 2013a,b; Ruane et al., 2013). RCPs 4.5 and 8.5 pathways, in which radiative forcing of GHGs reaches 4.5 and 8.5 W/m^2 in the year 2100 relative to pre-industrial levels respectively (Van Vuuren et al., 2011). The CO_2 concentration during near-term and mid-century for RCP4.5 and RCP8.5 were 423 and 499 ppm by 2025s and 2050s and 432 and 571 ppm by 2025s and 2050s respectively. A baseline CO_2 concentration of 380 ppm was used in this study (Rosenzweig et al., 2013). A detailed description of RCPs and CO_2 concentrations are available in AgMIP (2014) and Moss et al. (2010).

2.2.1.1. Statistical downscaling approach. To create mean and variability change scenarios, we employed stretched distribution approach that is related to quantile mapping (Ruane et al., 2015b). In this approach, in addition to changes in monthly mean Tmax, Tmin, and precipitation, changes have also been imposed on the standard deviation of daily Tmax and Tmin as well as upon the number of rainy days and the shape of the rainfall distribution. We imposed both mean and variability changes to adjust the monthly distribution of climate variables in a Gaussian fit (defined by mean and standard deviation) for Tmax and Tmin and a gamma distribution (defined by mean precipitation, the number of rain events, and a shape parameter) for rain events when they do occur (Wilks, 2011). In this way we stretched the historical time-series to mimic future projections where mean and variability changes have occurred. The climate outputs revealed the changes in variability parameters. Upon calculating monthly changes in the mean and standard deviation of temperatures, a target theoretical distribution was calculated. For precipitation, the number of rainy days were adjusted (by eliminating the driest days to reduce the total or by adding precipitation on the cloudiest days to add to the total) and the mean and shape parameter was allowed to calculate its own theoretical distribution. To generate the new downscale scenario, each event from the historical period is shifted according to the difference between the historical theoretical distribution and the future theoretical distribution. Temperature changes are added, while precipitation changes are adjusted using a multiplicative factor. The result is a new scenario with mean and variability parameters adjusted according to the imposed changes maintaining the historical signature of local differences between the true and theoretical distributions. This distribution stretching leads to a time-series that reflects how more extreme climate events change at a greater rate than the rate at which average events change.

2.2.2. Soil data and characteristics

The soil of the area is Himalayan alluvial, deposited by Ravi and Chenab rivers, loamy textured developed in a mixed calcareous with medium texture, very poor in organic carbon in different horizons (0.40–0.10) due to its oxidation promoted by high temperature while soil is also deficit in nitrogen (0.05%) which is decreased in subsoil (0.01%). Soil properties data and associated model input parameters are presented in Table 1. Free lime (CaCO3) occurs in the soil with low availability of soil phosphorus and micronutrients. Therefore, the soil fertility factor (SLPF) for this experiment was adjusted to 0.96 during model calibration. The experimental area is relatively flat with low runoff potential (SLRO = 25) and well-drained soil (SLDR = 0.6). The soil has a brown to dull yellowish brown color (10YR 4/3; soil albedo = 0.13) up to 105 cm depth. Soil samples to a depth of 125 cm were collected before cotton planting and were analyzed for physical,

chemical and hydrological properties. Soil samples were evaluated for nutrient analysis (N, P, K and micro nutrients), percent sand, silt and clay, pH, organic carbon, cation exchange capacity (CEC) and bulk density in different soil profile layers. Due to heterogeneity in soil properties, profile was divided in to six different soil master horizons layers (0–15, 15–30, 30–45, 45–60, 60–90 and 90–125 cm). Soil hydrological properties such as field capacity (drained upper limit = DUL), permanent wilting point (lower limit = LL), saturated hydraulic conductivity (SSKS) and saturated soil water content (SSAT) were computed (Table 1). Soil root growth factor (SRGF) was assessed using a function in CSM-DSSAT. Although soils are low in nitrogen due to high decay of soil organic carbon owing to high temperature in the region, nitrogen is being used for cotton growth and yield during model calibration. The S-build sub module in CSM-DSSAT was used for computation of soil properties. Soil parameters were then calibrated using an initial set of genetic coefficients.

2.2.3. Crop management practices and input data set for crop model

Crop management for all planting dates and growing season was considered to be the same. Cotton seed was sown on bed furrow planting method as it is a trend in Cotton-Wheat cropping system. Soil moisture in the soil profile was measured using neutron moisture meter and irrigation was applied according to crop requirements to avoid the water stress. All cultural and crop management operations for better crop production from sowing to picking and harvesting were adopted. The reader is referred to Rahman et al. (2016) for more detail. Crop phenological stages of cotton were recorded by randomly tagging five plants in each experimental unit to observe calendar time (photo thermal days) between different phenological phases up to cotton pickings and harvest. Photo thermal time (days) up to flowering, boll, seed, and boll maturity were used as input data set in model calibration. Three randomly selected plants from one meter in height were harvested at ground level with interval of 20 days after establishment of crop from each plot. The detailed methodology for TDM, peak LAI and temporal variation in LAI is available in Rahman et al. (2016).These data were used as input data set in the model during calibration and evaluation. Seed cotton yield, number of bolls and weight were computed during crop development, lint weight was measured for the purpose of ginning out turn (GOT) calculation. This was derived from the equation as; (lint weight/total seed cotton yield) × 100. Boll dry weight, seed cotton yield data was also recorded during crop development and boll dry weight at final harvest and during at different picking were used as PWAM and PWAD kg ha^{-1} in the model. Seed cotton yield (SCY) at final harvest and time series picking data was recorded for each experimental unit and used as HWAH and GWAD kg ha^{-1}. Unit cotton seed weight (WTPSD) and seeds number per boll at final picking were also used as input data set in the model. Portioning of assimilates between vegetative and reproductive parts is an important part off of model calibration. Cotton harvest index (HI) during crop development and maturity was computed as; [cotton seed weight (kg ha^{-1})/total biomass (kg ha^{-1})] and also used in model calibration and evaluation. Threshing percentage (THRSH) was computed as; [seed cotton weight/(dry boll weight)], it is also key data in calibration and it was also tested during model calibration and evaluation.

2.3. CSM-CROPGRO-cotton model

The DSSAT-CSM version 4.6 was used in this study (Hoogenboom et al., 2015) due to its broad range applicability in variable climatic conditions for different cropping systems worldwide. The CSM-CROPGRO-Cotton model was developed from the CROPGRO-Soybean model. A process oriented model within CSM-DSSAT computes cropping system process on daily basis and selected sub processes are also calculated at an hourly time step. The model simulates the carbon, nitrogen and hydrological processes in the soil plant systems as well as their transformation by utilizing mass balance principles within the cropping system (Jones et al., 2003). The model's dynamic simulation includes various developmental stages, growth rate and biomass portioning that are affected by weather and soil conditions. The CSM-CROPGRO-Cotton model simulates cotton growth and developmental stages (emergence, first leaf, first flower, first seed, first cracked boll (physiological maturity) and 90% open boll) based on photo thermal time or thermal heat unit accretion while soil, weather, management and cultivar genetic coefficients are used as input data set (Thorp et al., 2014). Light interception and canopy photosynthesis simulations are based on leaf level photosynthesis equations from the hedgerow model (Boote and Pickering, 1994) which consider the cotton row structure and canopy cover. Shortfall of water and nitrogen in soil layers is an indicator of stress computed by the model which ultimately cause a reduction in carbohydrate availability for plant growth. Carbon assimilates are partitioned to various plant components (leaves, stems, roots, bolls and cotton seed). Deficit and excess in soil water and nitrogen conditions are the cause of plant stress simulated by model. Water deficit conditions, normal aging, nitrogen remobilization, light stress and maturity lead to leaf senescence in cotton while both water conditions either excessive or deficit are the cause of root senescence. Detailed description related sub modules structure, integration, methodologies and other processes used in CSM-DSSAT can be found in the documentation (Hoogenboom et al., 2010).

2.4. Parameterization of CSM-CROPGRO-cotton model

Parameterization includes categorizing parameters in CROPGRO-Cotton model that would best predict cotton growth, development and productivity according to local climatic conditions at experimental sites. The model has specific parameters information related to crop in species and cultivar files which define day length sensitivity, and heat unit accretion required for each specific growth and development stage. It was parameterized for simulation of treatments studied during all growing seasons in field experiments. Crop management's inputs were quantified during field experiments and include initial field conditions, cotton planting details, fertilizer applications, irrigation schedules, tillage information, cotton picking and harvest dates. The CSM-CROPGRO-Cotton model was calibrated with measured data associated with April-20 planting which was estimated to characterize the minimum or no stress conditions during field experiments. Data from

Table 1
Soil physical, chemical composition and hydrological properties used in model as input soil data set.

Depth (cm)	SLCL (%)	SLOC (%)	SLSI (%)	SLHW	LL (cm cm^{-1})	DUL (cm cm^{-1})	SSAT (cm cm^{-1})	SBDM (g cm^{-3})	SLNI (%)	SSKS (cm h^{-1})	SRGF
0–15	22	0.46	43	8.2	0.136	0.302	0.428	1.48	0.05	0.54	1.00
15–30	24	0.42	34	8.0	0.123	0.293	0.451	1.40	0.04	0.46	1.00
30–45	26	0.28	45	8.1	0.118	0.286	0.435	1.39	0.03	0.41	0.865
45–60	26	0.19	45	8.2	0.120	0.295	0.435	1.39	0.03	0.43	0.804
60–90	18	0.16	32	7.6	0.110	0.260	0.420	1.43	0.01	0.59	0.732
90–125	16	0.14	32	7.6	0.069	0.172	0.420	1.43	0.01	0.59	0.116

SLCL = Clay contents in soil, SLOC = soil organic carbon, SLSI = silt contents in soil, SLHW = Soil pH in water, LL = lower limit, DUL = drained upper limit, SSAT = saturation, SBDM = soil bulk density, SLNI = soil total nitrogen concentration, SSKS = saturated hydraulic conductivity, SRGF = soil root growth factor.

five additional planting dates were used to assess the model performance. The calibrated model was further evaluated using one more year of data for all planting dates. Model calibration was used to optimize the most important parameters in soil and genotypes files under non-stress conditions, in such a way as to obtain the crop coefficients potential which improve the simulations. After adjusting soil parameters which reasonably affect cotton seed and biomass simulations, cotton genotype coefficients were calibrated. Each cotton cultivar genetic coefficients were obtained successively during this process; starting with phenological parameters related to cotton development as flowering, boll, seed and boll opening dates (EMFL, FLSH, FLSD, SDPM), followed by growth controlling genetic coefficients (FLLF), LFMAX and SIZLF) and at the end of this process, cultivar coefficient related to cotton seed, number and weight of seeds, boll weight and boll loads were calibrated (Hunt and Boote, 1998). Cultivars coefficients were calibrated using generalized likelihood uncertainty estimation (GLUE) approach and sensitivity analysis in cropping system model DSSAT, focused on the phenological parameters including photo thermal time between plant emergence and flower appearance (EM-FL), photo thermal time between first flower and first boll (FL-SH), photo thermal time between first flower and first seed (FL-SD), photo thermal time between first seed and physiological maturity (SD-PM), photo thermal time between first flower and end of leaf expansion (FL-LF). Growth parameters consist of LFMAX [maximum leaf photosynthesis rate at 30 °C, 350 ppm CO_2, and high light (mg CO_2 m^{-2} S^{-1})], specific leaf area of cultivar under standard growth conditions (SLAVR), maximum size of full leaf (SIZLF) and cotton seed yield and its components parameters include seed size (WTPSD), maximum fraction of daily growth that is partitioned to seed plus shell (XFRT), seed filling duration for pod cohort at standard growth conditions (SFDUR), average seed per boll under standard growing conditions (SDPDV), time required for cultivar to reach final boll load under optimal conditions (PODUR) and maximum ratio of (SCY/(SCY + shell)) at maturity (THRSH). A manual calibration technique (iterative approach; trial and error method) was followed once suitable combinations of genetic coefficients from GLUE and sensitivity analysis were obtained. Parameters were adjusted within the studied range and the effect of each genetic coefficient on the modeled process was studied by comparing measured versus simulated development, growth, cotton seed yield and its components through the use of statistical indicators of model performance.

2.5. Statistical analysis for model accuracy assessment

Model accuracy and reliability evaluation can be done by comparing simulated and observed studied parameters during calibration and evaluation by using statistical formula equations. The goodness of fit between simulated and measured values were determined with the percent difference (PD) using the following formula.

$$PD = 100 \times \frac{Simulated - Measured}{Measured} \tag{1}$$

PD indicates the deviation of simulated parallel to observed parameters, a negative change revealed under model prediction while positive change in PD value indicates over prediction of model values. Generally, correlation coefficient (r) and coefficient of determination (R^2) are used to assess the association between simulated and measured values. However, “the magnitudes of r and R^2 are not consistently related to the accuracy of prediction, i.e., where accuracy is defined as the degree to which model predictions approach the magnitude of their measured counterparts” and alone they are not sufficient to deduce any meaningful distinctions between the models (Willmott, 1982). Therefore, average error estimates in measured and simulated in-season biomass growth, biomass at harvest and grain yield were calculated using the index of agreement (d), root mean square error (RMSE), normalized root mean square error (NRMSE) and mean absolute error (MAE) as suggested by Willmott et al. (1985); Wallach and Goffinet (1989) and Loague and Green (1991) respectively, using the following relationships. The relative size of average difference and nature of the difference in time course simulation of crop biomass and yield, widely used descriptive measure for cross comparison i.e., Willmott index of agreement (d) was used in this study using the following equation;

$$d = 1 - \left[\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{\sum_{i=1}^{n} (|P'_i| - |O'_i|)^2} \right], \; 0 \le d \le 1 \tag{2}$$

Index of agreement (d) could be computed by using Eq. (2), where n is the observation number, P_i is the predicted assessment for the ith quantity while O_i is the observed one for the ith measurement. P'_i was calculaed as $P_i - \overline{O}$, and O'_i was computed as $O_i - \overline{O}$, while $\overline{O}$ is the mean observation. Its value ranges from 0 to 1, closer the d index values to unity (1), the better the fit and better model simulation.

$$RMSE = \sqrt{\left[\frac{\sum_{i=1}^{n} (X_s - X_o)^2}{n} \right]} \tag{3}$$

Root mean square error (RMSE) was used to decide the statistical differences between observed and simulated variables. RMSE was computed by using Eq. (3) to determine the degree of predictability (Soler et al., 2007). Where *n* denotes the observations number used for comparisons, XS are the simulated variables studied while Xo are the observed one used in the above equation.

$$NRMSE = \left[\frac{RMSE}{\overline{X}} \right] \times 100\% \tag{4}$$

The normalized root mean square error (NRMSE) was computed using above Eq. (4) while $\overline{X}$ was the mean observed values of studied variables as it gives a percent measure of the relative difference between simulated and measured values (Soler et al., 2007). RMSE is widely used for model accuracy evaluation and is considered as the standard for models testing (Kiniry et al., 1997) but NRMSE is better than RMSE because it provides the error level related to each evaluation between simulated and observed variables. Values < 10% are considered excellent prediction while > 10% < 20% good, > 20% < 30% are considered fair and > 30% indicate poor model performance (Jamieson et al., 1991). PD and NRMSE values of zero reveals that model simulation is excellent.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |X_s - X_o| \tag{5}$$

Mean absolute error was computed using Eq. (5), it indicates the difference between simulated and observed variables. It was used to detect whether simulated values were over- or under-estimated by the model.

2.6. Crop management scenarios under changing climate

Different management options/adaptation were developed and assessed for cotton crop under changing climate scenarios to overcome the negative impacts of climate change. Planting dates with weekly intervals from March to July were formulated in crop model and potential was assessed from simulation of baseline and climate change scenarios. Highest yield producing planting dates under changing climatic scenarios were considered. Nitrogen fertilizer levels i.e. low, moderate, recommended (180 kg N ha^{-1}), high and very high (no nitrogen limitation) were simulated for their potential to cope with climate change. We evaluated simulations under full irrigation and no nutrient limitation management strategies to get the optimum management adaptation to minimize the negative impacts of future climate. Effects of supplementary irrigation at cotton critical growth stages were assessed while reduced, current and higher amount of irrigation

application options were also evaluated to get the best management adaptation package. Different planting density options, lower and higher plants than recommended one (55,000 plants ha^{-1}) were also assessed to find the most optimum planting density under baseline and climate change scenarios. Genetic potential of cultivars with enhanced resilience against climate change would be consider an important adaption strategy. Virtual cultivars with different level of genetic potential were developed and simulations were evaluated under baseline

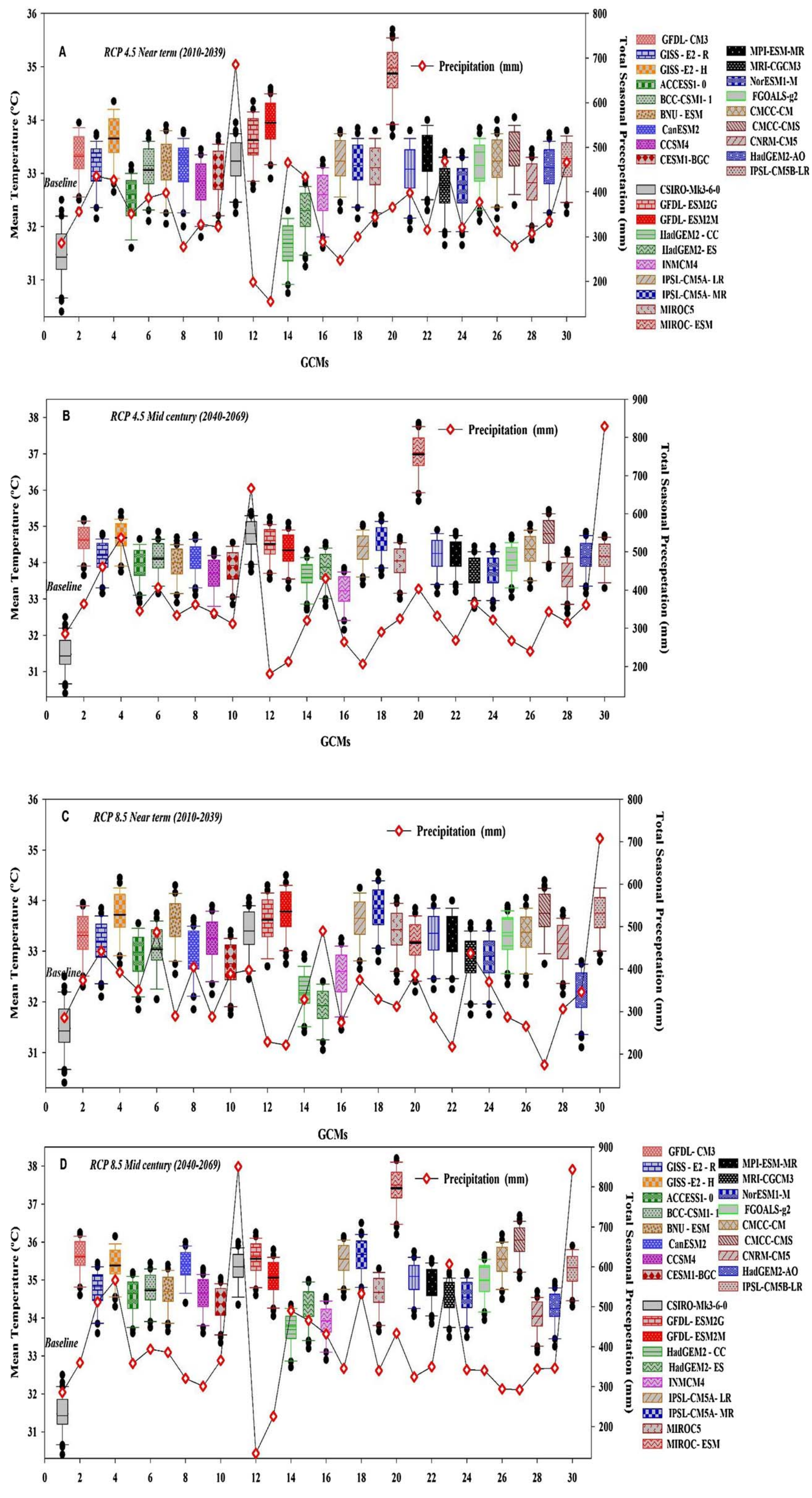

Fig. 1. Changes in mean seasonal temperature (°C) and total seasonal precipitation (mm) as projected by climate models relative to baseline period (1980–2010) under different representative concentration pathways (RCPs 4.5 and 8.5) during near term (2010–2039) and mid-century (2040–2069) time periods, respectively (A–D). A = RCP 4.5, near term (2010–2039), B = RCP 4.5 mid-century (2040–2069), C = RCP 8.5, near term (2010–2039), D = RCP 4.5 mid-century (2040–2069). Black dots in box plot represents the peak values on both ends, upper peak and lower values in the data set (30 years climatic data).

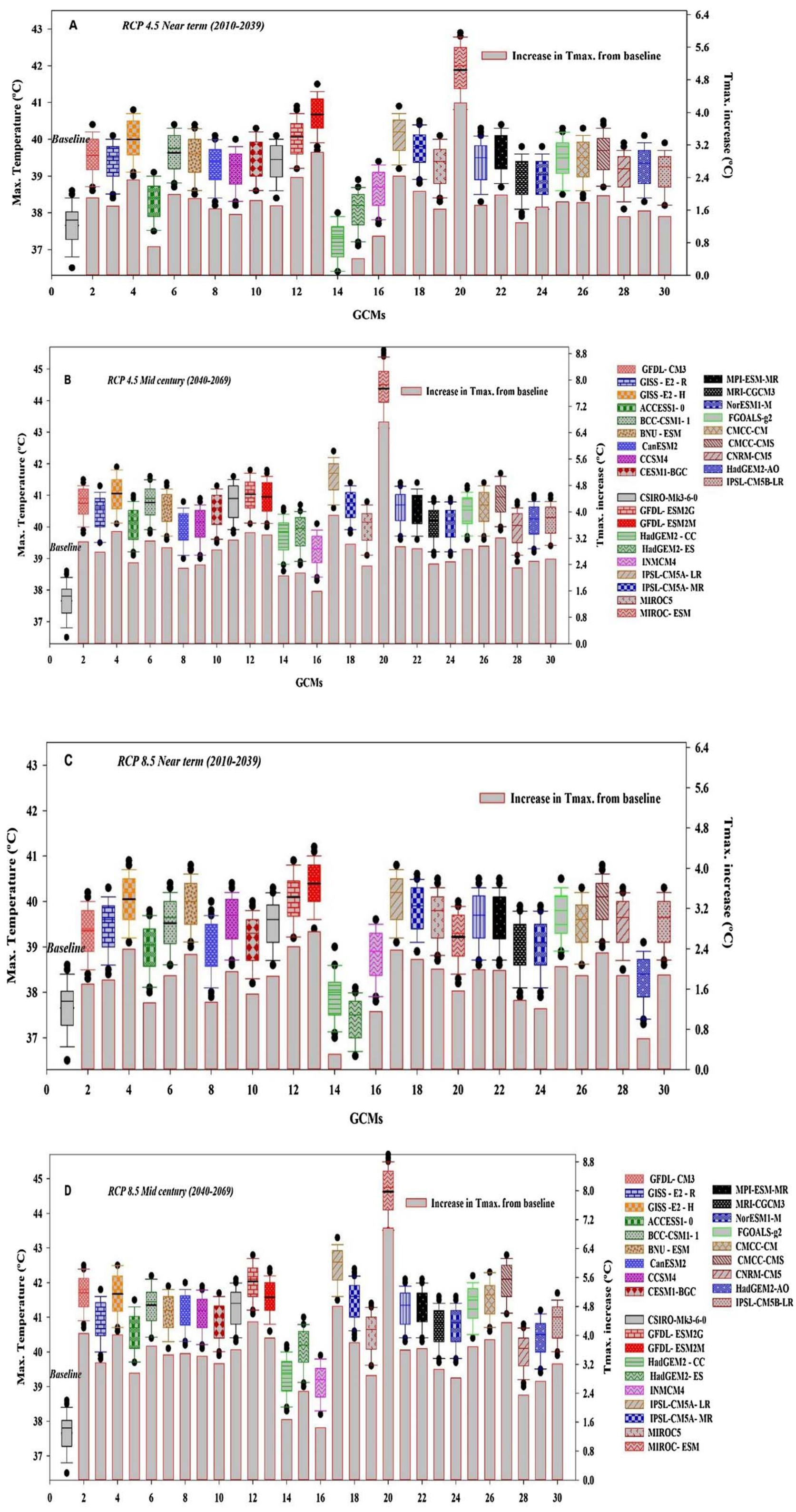

Fig. 2. Maximum seasonal temperature (˚C) and changes in maximum seasonal temperature (ºC) as projected by climate models relative to baseline period (1980–2010) under different representative concentration pathways (RCPs 4.5 and 8.5) during near term (2010–2039) and mid-century (2040–2069) time periods, respectively (A–D). A = RCP 4.5, near term (2010–2039), B = RCP 4.5 mid-century (2040–2069), C = RCP 8.5, near term (2010–2039), D = RCP 4.5 mid-century (2040–2069). Black dots in box plot represents the peak values on both ends, upper peak and lower values in the data set (30 years climatic data).

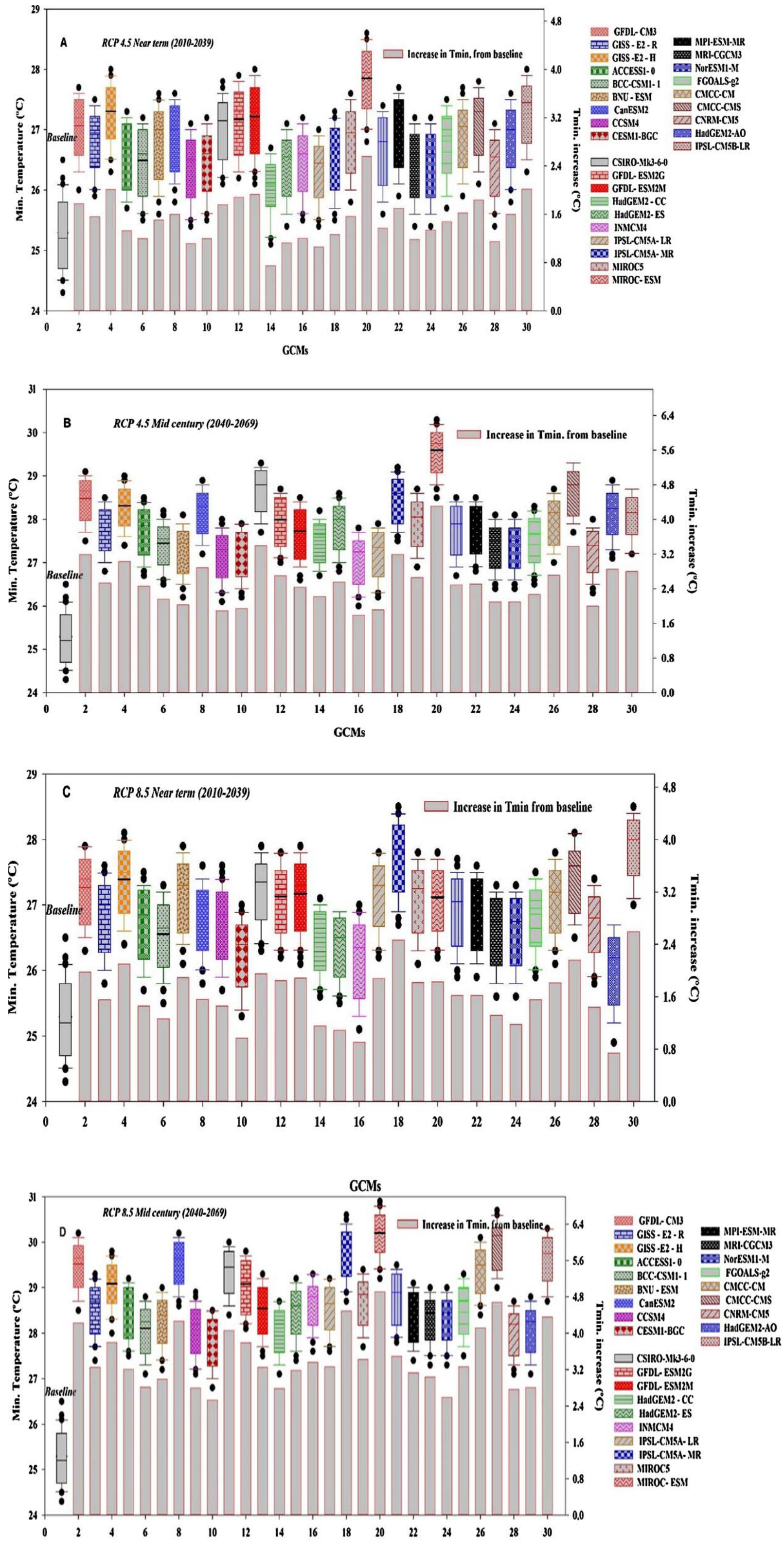

Fig. 3. Minimum seasonal temperature (°C) and changes in minimum seasonal temperature (°C) as projected by climate models relative to baseline period (1980–2010) under different representative concentration pathways (RCPs 4.5 and 8.5) during near term (2010–2039) and mid-century (2040–2069) time periods, respectively (A–D). A = RCP 4.5, near term (2010–2039), B = RCP 4.5 mid-century (2040–2069), C = RCP 8.5, near term (2010–2039), D = RCP 4.5 mid-century (2040–2069). Black dots in box plot represents the peak values on both ends, upper peak and lower values in the data set (30 years climatic data).

and climate change scenarios. Climate models with maximum consensus of temperature and rainfall in RCP 4.5 and RCP 8.5 in near term were used for this study while worst case scenarios were skipped to develop adaptation management options. Optimum level of each management (sowing date, fertilizer, irrigation, planting density and genetic potential) was combined to develop a complete adaptation package which has potential to cope the negative impact of climate in future.

3. Results and discussion

3.1. Climate change scenarios; projected changes in temperature and precipitation

The baseline average minimum and maximum daily temperature from April to October are 25.29 °C and 37.66 °C respectively, while mean seasonal temperature is 31.48 °C and seasonal precipitation is 286 mm. Climate change scenario projections reveal that there would be increase in minimum and maximum temperature, CO_2 and variability in rainfall pattern during cotton growing seasons both in the near term and by mid-century. The mean seasonal temperature is expected to increase by 1.64 °C and 2.75 °C in the near term (2010–2039) and mid-century (2040–2069), respectively under RCP 4.5 relative to the baseline (Fig. 1A and B). RCP 8.5 is associated with extreme temperature change; with a rise of 1.71 °C and 3.49 in the near term and by mid-century, respectively (Fig. 1C and D). The average seasonal maximum is expected to increase by 1.74 °C and 2.90 °C and minimum temperature by 1.50 °C and 2.57 °C in the near term (2010–2039) and mid-century (2040–2069), respectively under RCP 4.5 (Figs. 2 and 3A and B) while higher increase in maximum temperature (1.71 °C and 3.48 °C) and minimum (1.62 °C and 3.47 °C) are projected under RCP 8.5 emission scenario (Figs. 2 and 3C and D). Projected changes in seasonal precipitation include an increase of 25%–26% (near term) and 23%–43% (mid-century) relative to the baseline (286 mm) under RCP 4.5 and RCP 8. (Fig. 1A–D).

An important amount of variation was observed model-derived projections of mean temperature (Tmean.), maximum temperature (Tmax.), minimum temperature (Tmin.), and precipitation, which were classified into the following categories: moderate, hot dry, hot wet, cool dry, cool wet, moderate dry, moderate wet, very hot and dry. The smallest changes in seasonal average temperature relative to the baseline range from 0.57 °C (HADGEM2-CC) to 3.39 °C (MIROC-ESM), while the biggest changes are from 1.69 °C (INMCM4) to 5.51 °C (MIROC-ESM) under RCP 4.5 scenario. More extreme changes were found under RCP 8.5 scenario as climatic variables had wider ranges under RCP 8.5 than RCP 4.5 scenario. The smallest projected increases ranged between 0.42 °C (HADGEM2-ES) and 2.33 °C (IPSL-CM5A-MR) while the highest spanned 2.40 °C (INMCM4) to 5.94 °C (MIROC-ESM). Climate projections from HADGEM2-CC revealed that maximum temperature would decrease (0.41 °C) while MIROC-ESM is associated with an increase of up to 4.23 °C in the near term while INMCM4 and MIROC-ESM projected a higher increase (1.59 °C and 6.73 °C respectively) (Fig. 2A and B). Increase in Tmax would range −0.25 °C (HADGEM2-ES)–2.74 °C (GFDL-ESM2M) in the near term and from 1.45 °C (INMCM4) to 6.97 °C (MIROC-ESM) by mid-century under RCP 8.5 (Fig. 2C and D). Minimum temperature is expected to increase more than maximum temperature in both selected time spans. Only one climate model (HADGEM2) projected a decrease in maximum temperature. However, there is no single model projection showing a decrease in minimum temperature. The minor increase in minimum temperature (0.75 °C and 1.79 °C) is projected by HADGEM2-CC and INCMCM4 models while MIROC-ESM projects a higher increase (2.56 °C and 4.30 °C) under RCP 4.5 for the near term and mid-century, respectively (Fig. 3A and B). A high rise in minimum temperature is expected under RCP 8.5 than RCP 4.5 scenario in both time slices, with the lowest minimum rise 0.74 °C and 2.54 °C associated with HADGEM2-AO and CESM1-BGC climatic models and the highest increase (2.59 °C and 4.91 °C) is associated with IPSL-CM5B-LR and MIROC-ESM models for near term and mid-century, respectively (Fig. 3C and D). Projected changes in seasonal precipitation are the most variable and uncertain. Precipitation varies widely under emission scenarios and GCMs, fewer climate models (2–7) show reduction in seasonal rainfall (GFDL-ESM2M) in near term under RCP 4.5 scenario while highest reduction projected by GFDL-ESM2G under RCP 8.5 scenario during mid-century. Projections from the majority climate

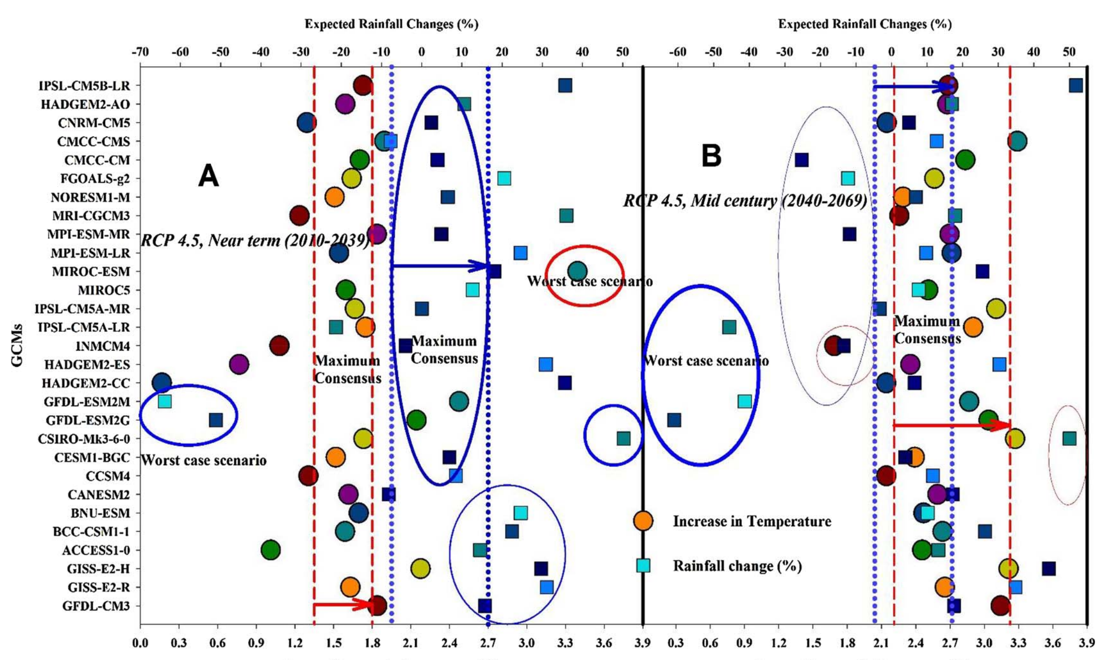

Fig. 4. Climate analysis; GCMs evaluation and categorization on the basis of changes in temperature (°C) and rainfall under RCP 4.5 in near term (A) and mid-century (B). Red and blue dotted lines and circles represents the temperature and rainfall respectively. Maximum consensus by the GCMs and worst case scenarios in temperature and rainfall are circled with red and blue color. For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

models reveal small increase relative to the baseline. A few models projected a significant increase (up to 558 mm) relative to baseline during mid-century under RCP 8.5 scenario (Fig. 1A and B). Under RCP 8.5, precipitation is expected to decrease by up to 111 mm (CMCC-CMS) and increase by up to 422 mm (IPSL-CM5B-LR) during near term, with more pronounced changes by mid-century (−153 mm (GFDL-ESM2G) and +558 mm for IPSL-CM5B-LR) (Fig. 1C and D). IPSL-CM5B-LR is wet and hot as well during all studied scenarios, compared to others models (GCMs).

Results of maximum consensus, worse and worst scenarios in GCMs and RCPs are presented in Figs. 4 and 5. Maximum consensus by GCMs under RCP 4.5 revealed the increase in temperature of 1.2–1.8 °C and 2.2–3.1 °C in near term and mid-century time periods, respectively (Fig. 4A and B). Similarly, rainfall changes are expected −8% to 15% and −5 to 17% in near term and mid-century time periods, respectively. GCM, like MIROC-ESM was found the hottest one with increase in temperature of 3.4 °C and 5.51 °C during near term and mid-century respectively and it may declare the worst case scenario in RCP 4.5. Furthermore, GISS-E2H (3.23 °C), CMCC-CMS (3.3 °C), CSIRO-MK3-6-0 (3.27 °C), GFDL-ESM2M (2.5 °C) and GFDL-ESM2G (2.14 °C) were found hotter and may pronounce as warmer GCMs. Generally, models showed the trend toward increase in precipitation (wet conditions) under RCP 4.5 scenario. Although few GCMs were found the drier ones compared with seasonal baseline like GFDL-ESM2G (−51%) and GFDL-ESM2M (−64%) in near term while GFDL-ESM2G (−61%), GFDL-ESM2M (−41%) and IPSL-CM5A-LR (−46%) in mid-century, respectively (Fig. 4A and Fig. 4B).

Changes in temperature and precipitation under RCP 8.5 scenario compared with baseline revealed maximum consensus affirm by GCMs, showed that 1.4–2.2 °C and 3.0–3.9 °C increase in temperature is expected in near term and mid-century, respectively. Rainfall changes would range −8 to 22% in near term and −2 to 20% in mid-century for RCP 8.5 scenario (Figs. 5A and B). Same GCMs were found hotter, worst and worse case scenarios here as well in RCP 8.5 like RCP 4.5 scenario, higher increase in temperature is expected in MIROC-ESM (5.94 °C), CMCC-CMS (4.52 °C), GFDL-ESM2M (4.10 °C) and GFDL-ESM2G (4.14 °C). Similarly, GFDL-ESM2M (−36% and −34%) and GFDL-ESM2G (31% and −76%) were found drier in both time periods while CMCC-CM5 (−67%) and MPI-ESM-MR (−40%) in near term under RCP 8.5 and these models may state as worst case scenarios (Fig. 5A and Fig. 5B). Furthermore, two models were found much wetter (> 25%) like IPSL-CM5B-LR and CSIRO-MK3-6-0 while GISS-E2-R, GISS-E2-H, BCC-CSM1-1 and GFDL-CM3 were found wetter (> 16%) in both RCPs 4.5 and 8.5 scenarios and time periods (near term and mid-century). Climate models like, CCSM4, HadGEM2-CC, HadGEM2-ES, INMCM4, CanESM2, CNRM-CM5, ACCESS1-0, BNU-ESM and MIROC5 are found less uncertain and showed stable behavior. Therefore, these models can be used for climate change impact assessment for other crops in the region.

Climate change impact assessment studies should not rely on only one GCM, as uncertainties in climate projections are common under emission scenarios (Wilby et al., 2004; Araya et al., 2015). Climate models with highly diverse characteristics lead to uncertainty and produce extremes results which may not accurately represent future climate conditions. The use of multiple models can provide more reliable decision support in climate change impact assessment and assessments of agricultural system vulnerability (Asseng, 2013; Rosenzweig et al., 2013; Wilby et al., 2009). Previous studies reveal that GCMs and RCPs are major source of uncertanities in climate change impact quantification because GCMs have a limited capacity to represent climate extremes and interannual climate variations which ultimately affect the crop growth process in crop models and lead to false represention of climate change impacts on crops (Asseng et al., 2014; Osborne et al., 2013; Kassie et al., 2015; Araya et al., 2015). GCMs can be used for climate change impact assessment with a certain degree of confidence (Asseng, 2013; Araya et al., 2015). Climatic models should be bias-corrected because climate change impact studies requires accurate and reliable climate change projections (Challinor

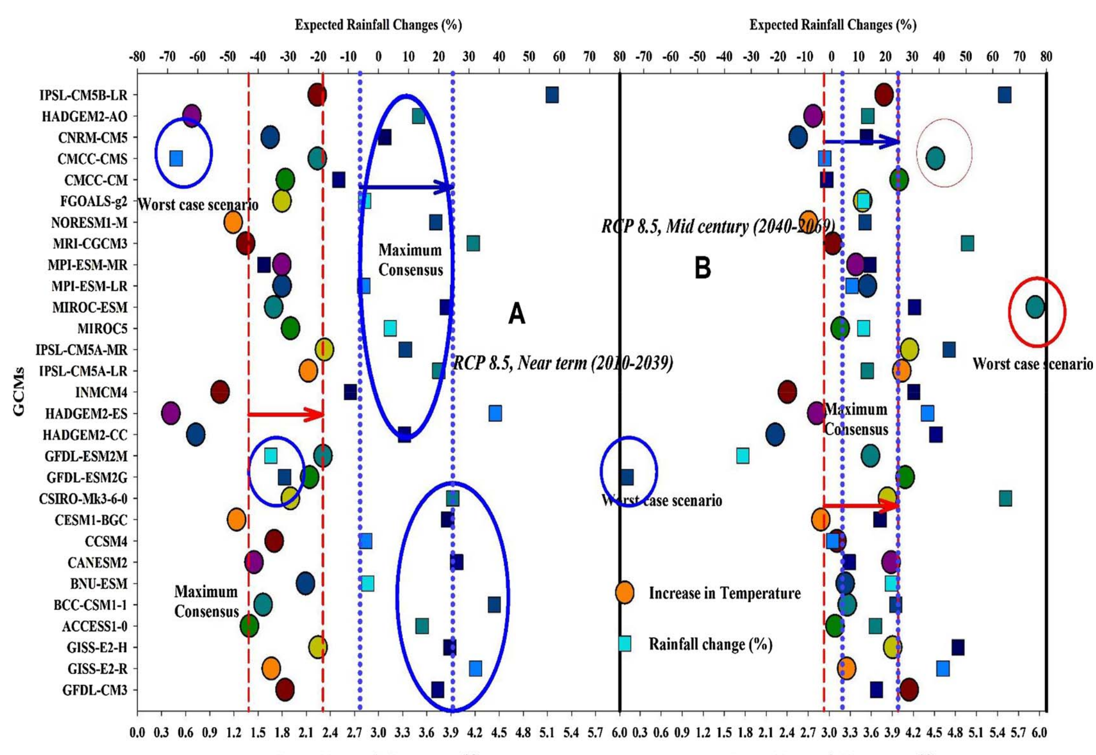

Fig. 5. Climate analysis; GCMs evaluation and categorization on the basis of changes in temperature (°C) and rainfall under RCP 8.5 in near term (A) and mid-century (B). Red and blue dotted lines and circles represents the temperature and rainfall respectively. Maximum consensus by the GCMs and worst case scenarios in temperature and rainfall are circled with red and blue color. For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

et al., 2013). Ahmad et al. (2015) used five general circulation models (GCMs) to generate future climate conditions and assessed the potential impacts of climate change on wheat and rice crops in the Rice-Wheat cropping system of Punjab, Pakistan. We used 29 available climate models across the world and two emission scenarios (RCP 4.5 and 8.5) in combination with a crop model to reliably and accurately assess climate change impacts on cotton production, and evaluate uncertainties in GCMs and RCPs.

3.2. Crop model calibration and evaluation

The model calibration process provided a set of genetic coefficients (GCs), those were estimated for all cultivars tested. Cotton phenology and development parameters were calibrated first while growth (LAI, TDM temporal changes) followed by yield-related attributes. Longer growing season cv. MNH-886 took more photo thermal days (PTDs) from planting to boll maturity (BM) and contributed higher growth and SCY than others, while NIAB-112 took 7 less photo thermal days being a short duration cultivar as compared with MNH-886. The reproductive duration of cultivars (flowering to boll maturity) ranged from 70–72 PTDs (Table 2). Default cotton GCs related to leaf growth, maximum leaf photosynthesis rate (LFMAX) affect photosynthesis in the leaf as well as carbon assimilation. Therefore a broad range of these GCs were tested, to improve simulation. Since it affects many parameters including LAI, canopy growth and evapotranspiration (ET), LFMAX was adjusted to 1.47, 1.42 and 1.11 (mg CO_2 m^{-2} s^{-1}) for MNH-886, NIAB-9811 and NIAB-112 respectively (Table 2). Comparison of observed and simulated LAI and top weight (Kg ha^{-1}) of cultivars with their predicted deviation and absolute error during model calibration are described in the Table 3. During calibration, simulated and observed time series of LAI and tops weight comparisons for three cultivars revealed that the best model fit, as indicated by reasonably high statistical indices values, coefficient of determination (R^2) and d-index, were close to one (0.98–0.99 and 0.97–0.99) while mean absolute error (MAE) was 0.16–0.28 and 390 to 621 kg ha^{-1} for LAI and TDM respectively (Fig. 6a–c). In addition, RMSE and normalized RMSE of LAI and TDM for all cultivars were also reasonably good [(0.23–0.33 and 8.20–9.60%) and 561–707 kg ha^{-1} and 7.12–10.32%)] for eight sample points during cotton growth season (Fig. 6a–c). Relative to simulated values, observed time series of boll dry weight and SCY (Kg ha^{-1}) of cultivars revealed the best model fit, with both higher d-index and R^2 close to one (0.97–0.99) while RMSE, nRMSE and MAE values were also lower; 342–426 Kg ha^{-1}, 8.26–9.43% and 150–543 Kg ha^{-1} for boll dry weight and 105–320 Kg ha^{-1}, 4.30–10.80% and 95–137 Kg ha^{-1} for SCY respectively (Fig. 6d–f).

The model simulations for major phenological events from planting to flowering and boll maturity revealed good predictions for all cultivars irrespective of the sowing windows. The model slightly under-estimated both number of days to flowering and boll maturity for early planting windows and over-estimated those for later planting windows. The relationship between observed and simulated number of days to flowering and boll maturity of all studied treatments revealed a good performance overall [(RMSE = 1.58–1.84, d = 0.94–0.95) and (RMSE = 2.38–4.45, d = 0.85–0.91)] while R^2 for all cultivars ranged 0.92–0.96 for days to flowering. The regression equation slope was not statistically different from one and the intercept was not statistically different from zero when tested at 5% probability (Fig.7a and b). A line of best fit between simulated and observed biomass at harvest, revealed that the best prediction was associated with cv. NIAB-112, with minimum nRMSE of 7.43% and higher d-index values (0.95). Biomass was also very well simulated for the cultivars MNH-886 and NIAB-9811, with a normalized RMSE of 9.14% and 9.72% respectively, as well as high d-index values (close to one) (Fig. 8a). Model capability for SCY simulations was very good overall, with lower values of nRMSE (9.52%, 6.70% and 6.75%) and higher values of d-index (0.90, 0.80 and 0.78) for cultivars MNH-886, NIAB-9811 and NIAB-112 respectively (Fig. 8b). Simulated SCY matched with observed values better than previous studies, reflecting a good calibration of yield related GCs (WTPSD and THRESH). More field observations were available, allowing for a more robust calibration.

Final boll dry weight at harvest was best predicted for cultivar NIAB-9811 with lowest nRMSE of 5.44% and higher d-index and R^2 close to one(0.94 and 0.83) for all planting dates and during both growing years. Generally, the model predicted well for MNH-886 and NIAB-112 cultivars at harvest with lower nRMSE (6.54% and 8.20%), R^2 (0.79 and 0.80) and reasonable higher d-index (0.93 and 0.90) respectively with all planting dates during both growing years (Fig. 9a). The relationship between predicted and observed peak LAI across all planting dates during both growing years showed that the model performed well for all cultivars, especially MNH-886, with lower values of nRMSE (9.0%) and high values of d-index (0.80). The model also performed well for NIAB-9811 and NIAB-112 (Fig. 9b). These results confirm that the CSM-CROPGRO-Cotton model has the ability to simulate the phenological events, growth (LAI and TDM) and yield attributes of cultivars planted at various dates under arid to semi-arid climatic conditions. CSM-CROPGRO-Cotton model was well parametrized using a high quality data set of field trials and estimated genetic coefficients (GCs) of cultivars simulated phenology, growth, seed cotton yield, yield components very well, with reasonably good statistical indices. Phenology-related GCs were different from those

Table 2
Genetic coefficients results of cultivars adjusted during CSM-CROPGRO-Cotton model calibration.

Parameters	Cultivar coefficients description	Calibrated value MNH-886	NAIB-9811	NIAB-112	Testing Range	Default Value
	Cotton phenology and development					
PL-EM	Thermal time between planting and emergence	5	5	5	4–8	4
EM-FL	Photo thermal time between plant emergence and flower appearance	45	44	42	36–48	38
FL-SH	Photo thermal time between first flower and first boll	12	13	13	08–17	12
FL-SD	Photo thermal time between first flower and first seed	23	20	17	12–25	15
SD-PM	Photo thermal time between first seed and physiological maturity	49	51	53	40–55	42
FL-LF	Photo thermal time between first flower and end of leaf expansion	70	71	70	40–80	75
	Cotton Growth					
LFMAX	Maximum leaf photosynthesis rate at 30 °C, 350 ppm CO_2, and high light (mg CO_2 m^{-2} S^{-1})	1.47	1.42	1.11	0.7–1.8	1.10
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm^{-2} g^{-1})	136	138	141	120–200	170
SIZLF	Maximum size of full leaf (cm^2)	280	264	290	250–350	300
	Cotton seed yield					
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	0.61	0.63	0.64	0.50–0.90	0.85
SFDUR	Seed filling duration for pod cohort at standard growth conditions	34	35	33	18–36	24
PODUR	Time required for cultivar to reach final boll load under optimal conditions	13.8	12.4	12.2	7–18	8
THRSH	The maximum ratio of (seed/(seed + shell)) at maturity	72.0	68.4	71.0	45–80	70

Table 3
Comparison of observed and simulated variables related to phenology, growth and cotton seed yield and yield components during model calibration.

Variables	MNH-886				NIAB-112				NIAB-9811			
	Obs.	Sim.	Abs. Err.	%Err.	Obs.	Sim.	Abs. Err.	%Err.	Obs.	Sim.	Abs. Err.	%Err.
Days to flowering	61	60	−1	−1.64	57	57	0	0.00	59	59	0	0.00
Days to boll maturity	158	154	−4.0	−2.53	151	148	−3.0	−1.86	154	152	−2	−1.30
LAI	4.88	4.86	−0.02	−0.41	4.30	4.33	0.009	0.23	4.64	4.61	−0.029	−0.65
TDM (Kg ha^{-1})	14067	14092	25	0.18	12066	12572	506	4.19	13200	13549	349	2.64
Seed Cotton yield (Kg ha^{-1})	4545	4606	61	1.34	3979	3805	−174	−4.37	4287	4211	−76	−1.77
Seeds number (m^{-2})	3788	3595	−193	−5.10	3980	3843	−137	−3.44	3613	3580	−33	−0.91
Unit weight (g)	0.0770	0.0764	−0.0005	−0.78	0.066	0.0640	−0.0019	−2.88	0.075	0.072	−0.002	−2.93
Dry Boll weight (Kg ha^{-1})	6603	6480	−123	−1.86	5536	5283	−253	−4.57	6138	6076	−62	−1.01
Threshing%	70.12	71.06	0.94	1.34	71.87	72.01	0.139	0.19	69.88	69.36	−0.58	−0.83

previously reported by Wajid et al., (2014); Ahmad et al., (2017) for locally grown unpromising indigenous cultivars. However, these phenological parameters are in range with those previously determined by (Ortiz et al., 2009) and Thorp et al. (2014). Genetic coefficient XFRT, SFDUR, PODUR and THRESH provided a better fit for SCY and yield components and ultimately generated good predictions, indicating the model's good performance during calibration and evaluation for all studied parameters. Genetic coefficient varied among cultivars and also across environmental conditions as reported by Pathak et al. (2007); Zamora et al. (2009); Paz et al. (2012) and Modala et al. (2015). The CSM-CROPGRO-Cotton model was also reported to perform well (MPD < 1.59% and RMSE < 1.64 days) for cotton phenological events, growth and yield for two different plating dates and cultivars (Wajid et al., 2014). Seed cotton yield and tested yield components were predicted well for all studied planting dates and cultivars. Model prediction was in range with the observed and generated similar trends as field observations, indicating the model's ability to simulate yield attributes well. The results agree with a previous research study that revealed that the model can simulate boll dry weight and its dynamics fairly well, RE range −3.9% to 12.7% and had good values of d-index (0.63–0.86) for different treatments tested during evaluation (Ortiz et al., 2009). In general, the model simulated fairly well SYC dynamics for most of the planting dates as previously documented by Wajid et al. (2014) for SCY at final picking with lower MPD of 5.30% and 4.38% during calibrated and evaluated years respectively, for two plating dates with cultivars. Seed cotton yield under prediction were also

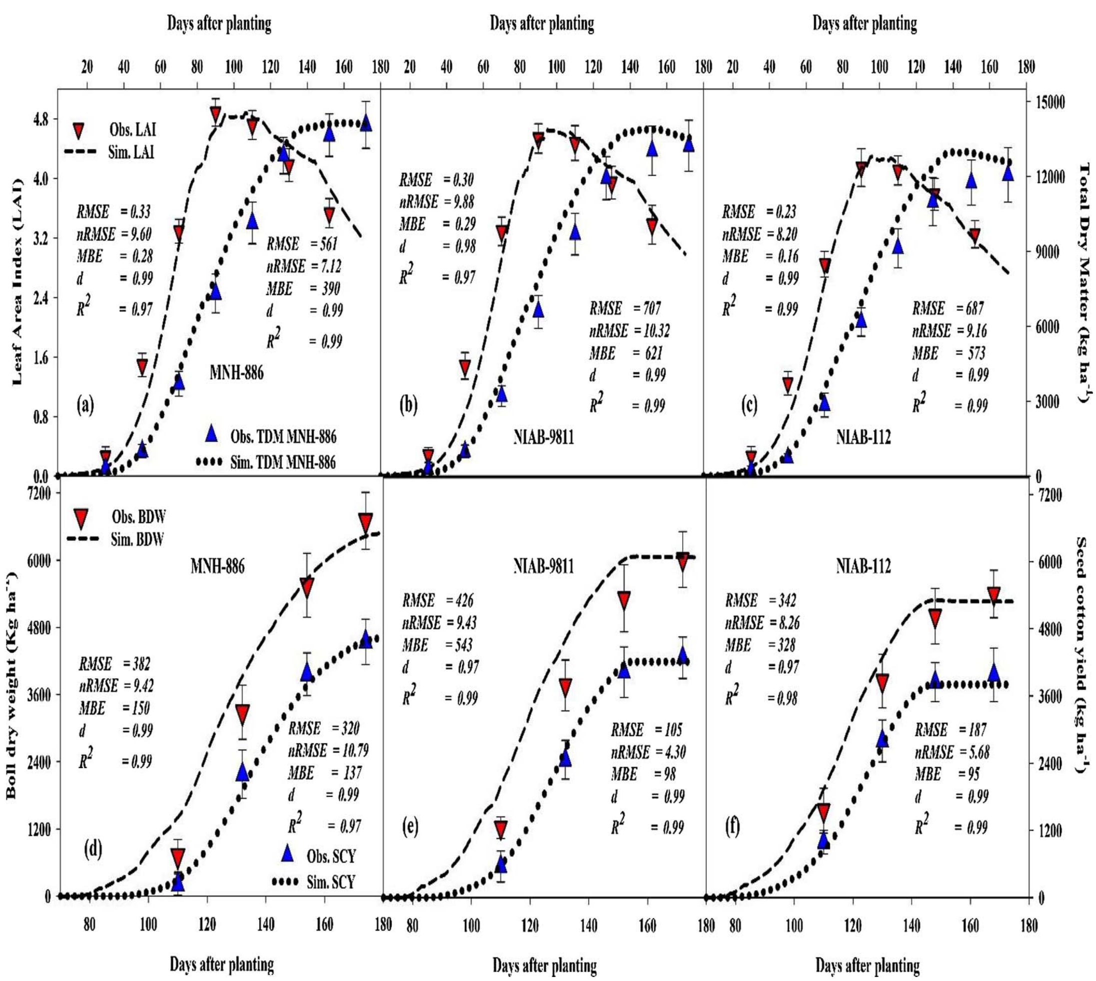

Fig. 6. Simulated and observed time series LAI, TDM (a–c) and boll dry weight (BDW), seed cotton yield (SCY) (d–f) of cultivars, MNH-886, NIAB-9811 and NIAB-112 during CSM-CROPGRO-Cotton model calibration.

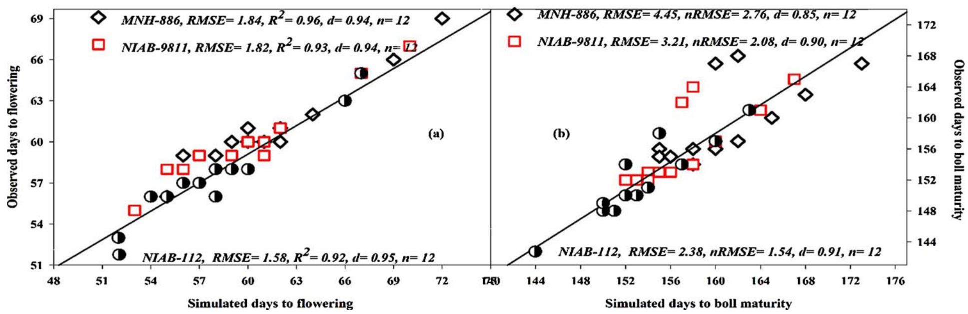

Fig. 7. CSM-CROPGRO-Cotton performance in phenology (days to flowering and boll maturity days) of cultivars planted at variables dates (10-March–21 June) during model evaluation.

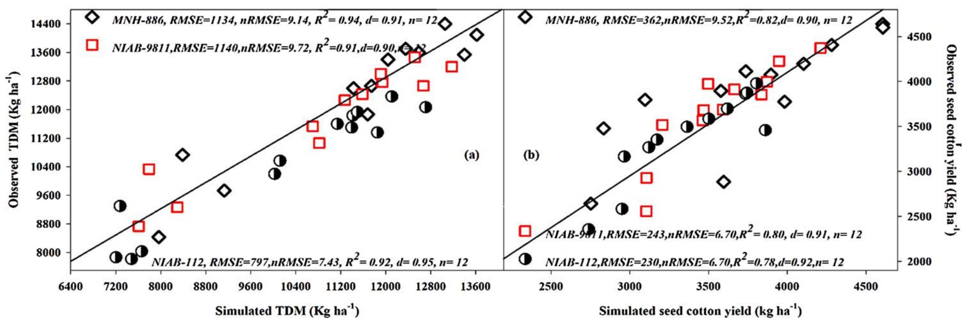

Fig. 8. CSM-CROPGRO-Cotton performance for TDM and seed cotton yield (Kg ha^{-1}) of cultivars planted at variables dates (10-March–21 June) during model evaluation.

documented by Modala et al. (2015) for ET replacement treatments (0, 33 and 133) during model evaluation with higher percent error of −56.9%, −32.2% and −23.9% respectively in Texas Rolling plains region. It is first study conducted to test thermos temporal and photo thermal responses for longer planting windows (March–July) for SCY while previous were limited to few planting dates (Wajid et al., 2014). It seems from results of this study and previous research work of Iqbal (2011) and Wajid et al. (2014) that CSM-CROPGRO-Cotton model could be successfully applied for different cotton management practices evaluation in semi-arid environmental conditions of Punjab.

3.3. Model sensitivity related carbon dioxide, temperature, water and nitrogen (CTWN-analysis)

The response of the calibrated model to carbon dioxide (CO_2), temperature, water and nitrogen was assessed to quantify model sensitivity. Relative to a baseline of 360 ppm, elevated CO_2 significantly enhanced yield up to 630 ppm; with the steepest increase occurring up to 540 ppm. CO_2 elevation of 630–720 ppm resulted in no significant difference in yield (Fig. 10). The model is less sensitive to elevated CO_2 than to temperature. A 2 °C increase in maximum and minimum temperature resulted in a significant drop in cotton yield. A 4 °C increase in maximum and minimum temperature resulted in only10% of the yield obtained than baseline temperature, and any further increase in temperature led to a complete loss in cotton yield (Fig. 11). Yield is more sensitive to nitrogen application; a significant increase in cotton yield was revealed with nitrogen application of up to 180 kg N ha^{-1} (Fig. 11). A steepest increase in cotton yield was observed at lower N increments (0 to 120 kg ha^{-1}) with a decrease occurring at higher N increments (120–210 kg ha^{-1}). The reason behind this may be that the soil is already deficient in nitrogen (0.05%) which is even lower in the subsoil (0.01%). Sensitivity to precipitation is not high, possibly because the model was calibrated in irrigated conditions. As such there was no water stress during the cotton growing season, rainfall 100% change in precipitation contributed to seed cotton yield while only a minor increase is observed with more pronounced changes in rainfall (125%–200%) (Fig.10). The model was calibrated under hot climatic conditions where maximum temperature get up to 48 ± 2 °C during the cotton growing season. This resulted in a smaller response to elevated CO_2 than to temperature. Although CO_2 fertilization has a positive effect on growth and yield of cotton by increasing photosynthesis, radiation and water use efficiency lead to increase in cotton yield (10–30%) by improving water use efficiency and decreasing stomatal conductance and transpiration (Reddy et al., 2002; Williams et al., 2015; Paz et al., 2012; Hatfield and Prueger, 2015; Adhikari et al., 2015). There are many uncertainties in inferring cotton response to CO_2 due to other limiting factors and interactions, especially temperature. A doubling of CO_2 does not improve the negative impact of temperature

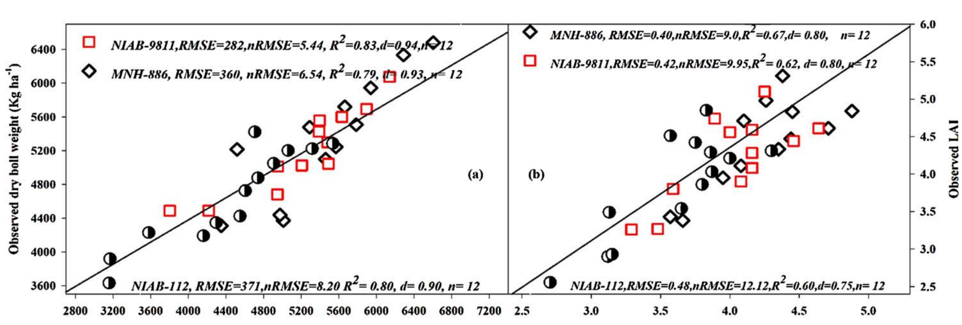

Fig. 9. CSM-CROPGRO-Cotton performance for dry boll weight (Kg ha^{-1}) and LAI of cultivars planted at variables dates (10-March–21 June) during model evaluation.

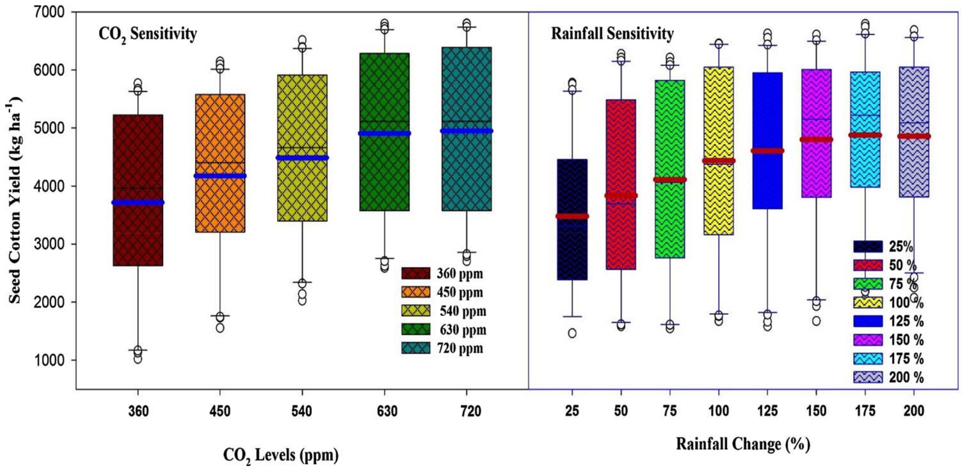

Fig. 10. Seed cotton yield (kg ha^{-1}) sensitivity to different CO_2 level and changes in rainfall (25–200%) simulated by calibrated CSM-CROPGRO-Cotton model.

on cotton growth (Reddy et al., 2004). Cotton yield severely decreased with an increase in temperature when daily mean temperature exceeds 32 °C (Schlenker and Roberts, 2009). This is due to a decrease in photosynthesis, an increase in respiration and evapotranspiration and accelerating the growth and development, which ultimately reduced the overall crop cycle and reproductive duration of boll development (Reddy et al., 2005; Luo et al., 2014). Nitrogen plays a crucial role in plant growth and yield and nitrogen sensitivity is a good indicator for model calibration assessment (Jones et al., 2003; Thorp et al., 2014).

3.4. Climate change impact quantification, scenarios comparison, models uncertainties evaluation and management adaptations under changing climate scenarios

Cotton is sensitive to variations in climatic conditions especially temperature and rainfall, especially during sowing, early vegetative growth and during reproductive stages. High temperature generally shortens the crop growth phases by speeding up cotton development, resulting in a negative impact on reproductive phases and ultimately yield and quality. Planting date is crucial in semi-arid to arid areas of the country because seed cotton yield losses are associated with inappropriate planting time under changing climate scenarios. Most climate change scenarios projected a reduction in mean cotton yield of cultivars relative to the baseline, exception made for two climate models (HADGEM2-CC and HADGEM2-ES) in the near term. Uncertainty is higher among GCMs as discussed in the above section. An important amount of variation (−1 to −45%) was also observed in SCY reduction relative to baseline under RCP 4.5 scenario in the near term (Fig. 12). Twenty seven GCMs projected a reduction in cotton yield while on average the 29 GCMs projected 8% reduction in mean cotton yield. The following three GCMs; GFDL-ESM2M, GFDL-ESM2G and MIROC-ESM predicted the highest mean yield reduction (45%, 28% and 39%) possibly because of warmer and drier environmental conditions during the cotton growing season. These three models project a 3.02 °C, 2.41 °C and 4.23 °C increase in maximum (daily) temperature and a 1.93 °C, 1.88 °C and 2.56 °C increase in minimum (night) temperature in the near term under RCP 4.5 emission scenario (Figs. 2 and 3A). These GCMs project drier conditions than the others, with 155 mm, 198 mm and 366 mm below potential evapotranspiration, which would cause drought conditions in combination with higher temperature during day and especially night lead to higher yield reduction in these three GCMs during near term (2010–2039). A more important reduction in seed cotton yield is expected in mid-century (2040–2069) due to a steeper projected increase in temperature and decrease in rainfall. There would be 20% reduction in mean seed cotton yield in mid-century as compared with seasonal average baseline (4147 kg ha^{-1}), ranging between −5% and 70% (Fig. 13). Higher average seasonal yield reduction (43%, 35% and 70%) is observed for the same GCMs as in near term for RCP 4.5 emission scenario. These GCMs project very hot conditions while the former two (GFDL-ESM2M, GFDL-ESM2G) project drier conditions than the later one (MIROC-ESM) is hottest and dry than all other. Higher increase in day temperature (3.30 °C, 3.37 °C and 6.73 °C) while 2.44 °C, 2.70 °C and 4.30 °C in night temperature is projected which ultimately lead to higher yield reduction (Figs. 2 and

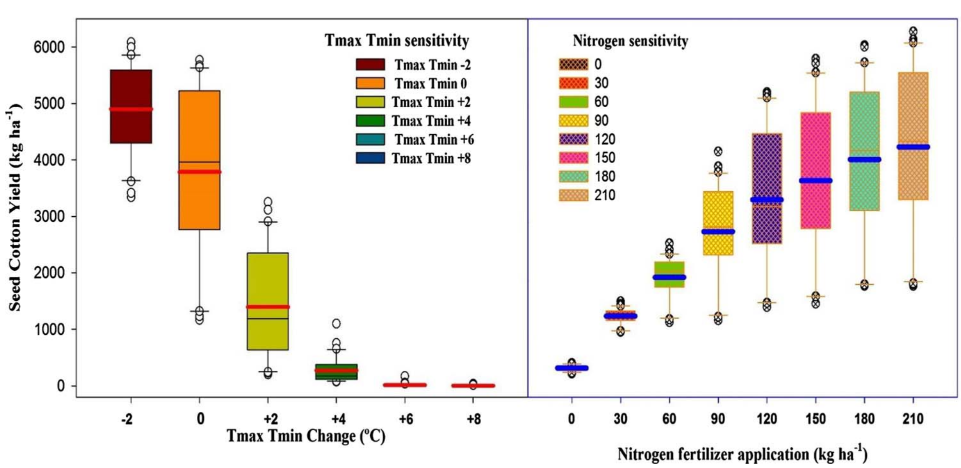

Fig. 11. Seed cotton yield (kg ha^{-1}) sensitivity to changes in maximum and minimum temperature (Tmax And Tmin) and nitrogen increments (0–210 kg ha^{-1}) simulated by calibrated CSM-CROPGRO-Cotton model.

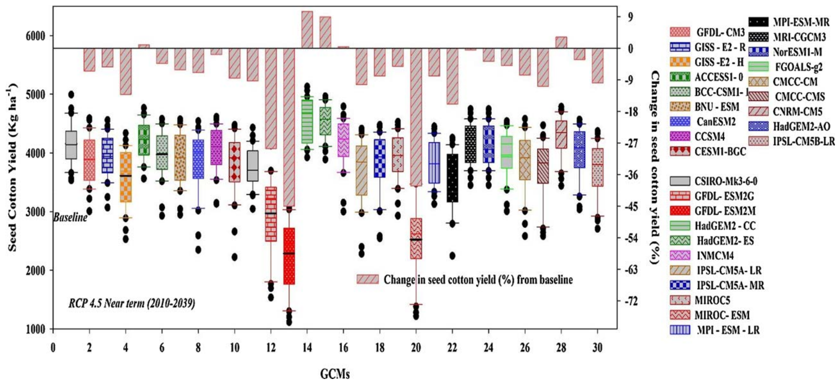

Fig. 12. Mean seed cotton yield (kg ha^{-1}) of cultivars and yield change (%) as compared with baseline (historic) simulated by CSM-CROPGRO-Cotton based on 29 GCMs under RCP 4.5 for near term of the 21st century (2010–2039).

3B). Uncertain low seasonal rainfall (181mm, 212 mm and 403mm) during cotton growing season also played a detrimental role. CCSM4, HADGEM2-CC, HADGEM2-ES, INMCM4 and CNRM-CM5 are associated with a lower SCY reduction because projected changes are not as severe, with > 300 mm rainfall during cotton growing season. The observed mid-century increase in maximum (1.59–2.39 °C) and minimum temperature (1.79 °C–2.55 °C) for these GCMs is also lower under RCP 4.5 (Figs. 2 and 3B).

Climate change results associated with RCP 8.5 emission scenario revealed 10% mean cotton production loss is expected in near term as compared with RCP 4.5 (Fig. 14) due to changes in temperature, especially minimum temperature (night) and drier spell. Overall, average seasonal maximum and minimum temperature projections across the 29 GCMs increase up to 1.71 °C and 1.62 °C respectively during near term period (Fig. 2 and 3C). Drier conditions are also projected, which combined with rising seasonal temperatures, would ultimately lead to higher yield reduction. Higher mean SCY reduction (16%–19%) is expected in CMCC-CMS, IPSL-CM5B-LR, GISS-E2-H, GFDL-ESM2M and GFDL-ESM2G while mean SCY would increase in HADGEM2-ES (1%) and HADGEM2-CC (4%) compared to the average seasonal baseline (Fig. 14). GFDL-ESM2M and GFDL-ESM2G are hotter and drier while HADGEM2-ES and HADGEM2-CC are milder but wetter (328 mm and 490mm) during cotton growing seasons, leading to less SCY reduction would occur. Higher cotton yield reduction (30%) is recorded during mid-century under RCP 8.5 due to increasing temperature and drier environmental conditions (Fig. 15). Results of climatic variables in mid-century revealed that there would an almost equal rise in day (Tmax.) and night temperature (Tmin.) 3.48 °C and 3.47 °C, respectively, higher rise in night temperature is detrimental for cotton production especially during reproductive phases which lead to the shedding of fruiting parts. Large variation among GCMs is found in mid-century as well, higher reduction due to harsh behavior of GCMs is expected for all cultivars. Mean cotton yield reduction of all cultivars, indicated that there would be 1% (HADGEM2-CC) to 70% (MIROC-ESM) reduction in cotton yield is expected during mid-century for RCP 8.5 emission scenario and mean ensemble reduction of 29 GCMs is 30% (Fig. 15). Generally ten GCMs (MIROC-ESM, GFDL-ESM2G, GFDL-ESM2M, IPSL-CM5A-LR, CMCC-CMS, GFDL-CM, CSIRO-MK3-6-0, MPI-ESM-MR, CANESM2 and IPSL-CM5A-MR) project severe changes, four GCMs (HADGEM2-CC, INMCM4, HADGEM2-ES and CNRM-CM5) project mild changes while all others, projected changes are moderate (Fig. 15). GCMs named GFDL-ESM2G, GFDL-ESM2M are very hot and drier while HADGEM2-ES, HADGEM2-CC and INMCM4 are also hot but wet lead to less cotton yield reduction for these GCMs. IPSL-CM5A-LR projected 50% yield reduction because maximum and minimum temperature are expected 4.81 °C and 3.26 °C respectively which lead to higher yield reduction. MIROC-ESM and GFDL-ESM2G showed higher SCY reduction due to higher rise in maximum and minimum temperature (6.97 °C and 4.38 °C, 4.91 °C and 3.80 °C) in mid-century under RCP 8.5 emission scenario (Figs. 2 and 3D).

As an adaptation strategy, sowing cotton five weeks earlier than the current planting date (10-May) was found effective which enhanced the seed cotton yield and it would compensate the negative impact of climate change in both scenarios during near-term. Optimum sowing dates which produced the maximum seed cotton yield occurred between 15 March and 30 March and this period found the most optimum to reduce the vulnerability of harsh weather. Early planting of cotton crop ensure early completion of vegetative growth phase and initiation of reproductive phases before the onset of harsh weather especially temperature and heat waves. It appeared that early sowing of cotton has an advantage in reducing heat stress in June and July and it has more potential than other management options. Generally, increasing the nitrogen rate up to 250 kg ha^{-1} increased seed cotton yield in both concentration pathways during near term, however highest dose of

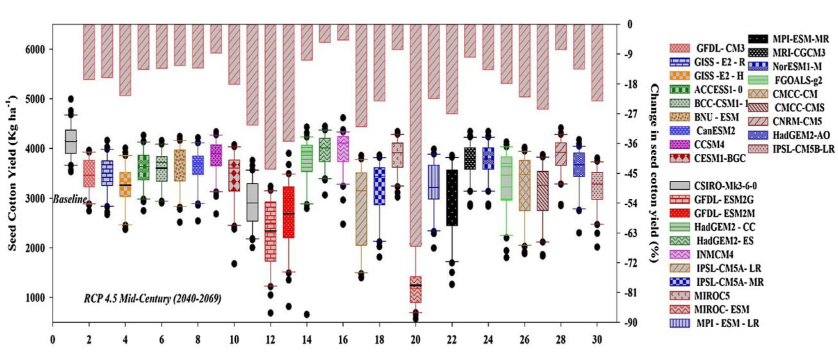

Fig. 13. Mean seed cotton yield (kg ha^{-1}) of cultivars and change (%) as compared with baseline (historic) simulated by CSM-CROPGRO-Cotton based on 29 GCMs under RCP 4.5 for mid of the 21st century (2040–2069).

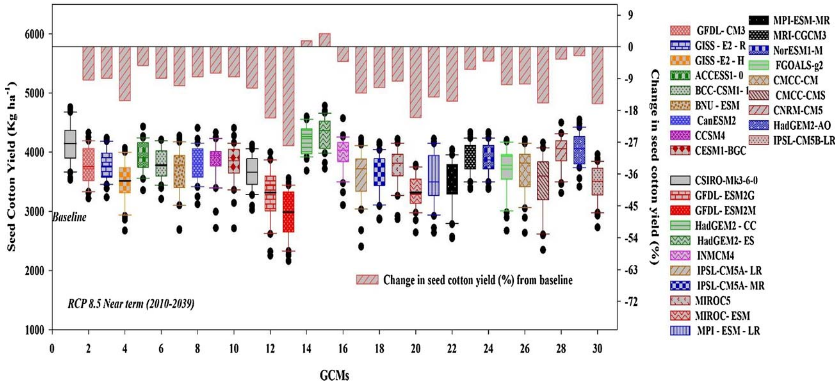

Fig. 14. Mean seed cotton yield (kg ha^{-1}) of cultivars and change (%) as compared with baseline (historic) simulated by CSM-CROPGRO-Cotton based on 29 GCMs under RCP 8.5 for near term of the 21st century (2010–2039).

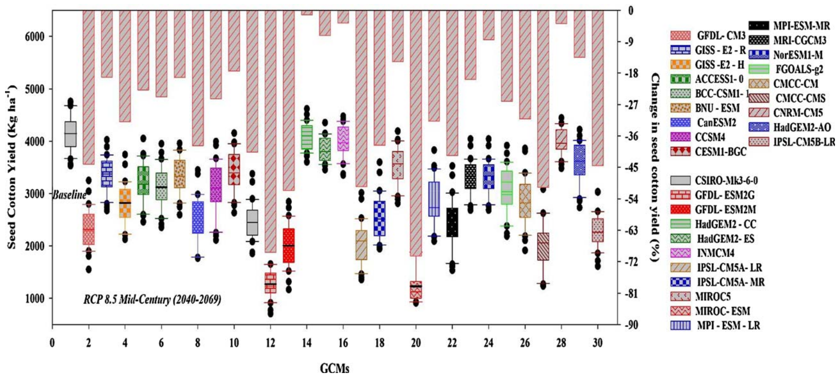

Fig. 15. Mean seed cotton yield (kg ha^{-1}) of cultivars and yield change (%) as compared with baseline (historic) simulated by CSM-CROPGRO-Cotton based on 29 GCMs under RCP 8.5 for mid of the 21st century (2040–2069).

nitrogen provided less addition in seed cotton yield. More seed cotton yield was produced in baseline than climate change scenarios. Moreover, 30% increase in current nitrogen amount has potential to enhance the cotton yield but higher increase did not contribute significantly in yield. It is suggested that cotton yield is less responsive to nitrogen than planting dates under changing climatic scenarios. Increase in irrigation amount resulted modest increase in cotton yield, while it did not increase yield significantly under wet and wetter GCMs. More increase in yield was observed under baseline than climate change scenarios. It is revealed that irrigation is modest effective under climate change. Furthermore, it enhanced yield under dry and drier GCMS like GFDL-ESM2M, GFDL-ESM2G, CMCC-CM5 and MPI-ESM-MR. Same irrigation as current amount (700 mm) with split irrigations at critical growth stages was found effective (+7% increase in yield) under climate change scenarios. It seemed that irrigation management did not have significant potential to cope with negative impact of climate change. Changes in plant population was found effective under climate change scenarios, higher level of planting density up to 18% and 30% for spreading and erect type of cultivars, respectively enhanced more yield in future scenarios than baseline. Planting density was found the second most important adaptation options in cotton management which has potential to cope the negative effect of climate change. Virtual cultivar with different genetic potential was assessed and evaluated for the potential against climate change. Seed cotton yield was significantly increased by enhancing genetic potential of cultivars under both climatic scenarios. Increase in genetic potential up to 17% than in combination with other optimum management as discussed above would generally be a suitable adaptation crop management strategy for the projected climate change.

We tested all available climate models (GCMs) and emission scenarios of RCP 4.5 and RCP 8.5 in combination with crop model for near term (2010–2039) and mid-century (2040–2069) for uncertainties analysis in climate change impact assessment. This multi climate model approach provides better information and reliable results for future in changing climate, and more reliable decision support for crop management (Asseng, 2013; Rosenzweig et al., 2013). Our climate change scenarios uncertainties analysis revealed that future seed cotton yields are likely to be negatively affected. Generally, the methods, tools, techniques and processes used in climate change impact quantification are all sources of uncertainty (Osborne et al., 2013; Whitfield, 2013). In our study, uncertainty is associated with climate models (GCMs) projections and emission scenarios (RCPs). Results confirmed that yield varies +9% to −45% and −5% to −70% in near term and mid-century, respectively under RCP 4.5 and in the same way −4% to −19% and −1% to −70% under RCP 8.5 for the same time slices. Emission scenarios contributes −8% to −10% and −20% to −30% uncertainty for near term and mid-century time slices respectively. Climate models (GCMs) are the main source of uncertainty in climate change impact assessment and these results are consistent with other studies of regional climate change impact quantification of other crops (Kassie et al., 2015; Araya et al., 2015; Yang et al., 2014). An analysis based on too few climate models (GCMs) may result in more uncertainty in future climate conditions, which, in turn may misguide stakeholders trying to minimize the negative impact of climate change (Wilby et al., 2004; Asseng et al., 2014).

Climate variables, especially rising maximum and minimum temperatures played crucial role in cotton yield reduction and negatively impact cotton growth by shortening the reproductive phases and enhancing transpiration rate as previously reported (Reddy et al., 2005). Previous study revealed that mean temperature of 26–28 °C is suitable for favorable growth of cotton and a decrease in cotton yield occurs when it exceeds 32 °C (Reddy et al., 2004). A rise in maximum

temperature of up to 5 °C reduced growing length by 35 days from emergence to maturity and even a doubling of CO_2 concentrations cannot reverse the adverse effects of high temperatures on cotton fruit retention (Reddy et al., 2005). Seed cotton yield has strong negative relationship with increasing temperature, which varies depending on the growth stage. Previous studies showed that higher rainfall during cotton growing season had negative impact (Yang et al., 2014). Temperature extremes during cotton reproductive phases reduced boll retention and mean temperature above 33 °C severely affect boll retention (Bange and Milroy, 2004). CO_2 fertilization has a beneficial effect on vegetative growth and biomass accumulation and yield but temperature has a strong negative impact which ultimately leads to seed cotton yield reduction. Reproductive phases are very sensitive to rises in temperature, causing fruit production efficiency to decline sharply (Reddy et al., 2005). CO_2 fertilization lead to increase in cotton productivity (40%) by enhancing photosynthesis and reducing stomatal conductance, transpiration and water losses which ultimately leads to higher water and radiation use efficiencies (Kimball et al., 2002; Williams et al., 2015). A rise in temperature has a negative impact on cotton growth and yield, it was also reported by Iqbal, (2011) in semiarid to arid environmental conditions in the region using DSSAT (v 4.3) environmental modification in seasonal analysis tool by using data of A2 and B2 scenarios for mid-century. Our results are in accordance with this study but we applied a rigorous methodology of climate models GCMs and RCP for near and mid-century for this important cotton growing region. This study also reported that there would be seed cotton yield reduction with increasing temperatures (1.8 °C relative to baseline) while with increasing or decreasing rainfall by 6% drastic yield reduction was observed. This proved that excessive rainfall also has negative impact on cotton yield by promoting vegetative growth and biomass and ultimately reduces yield. These results are in line with the findings of this study, in which we show that intensive and erratic rainfall would lead to negative impact on cotton.

These results are in range with the previous findings from a study conducted in India, where a 9% reduction in cotton yield would be expected under the scenario of a 4 °C rise in average temperature and decrease in precipitation using CO_2 360–540 ppm by adopting GOSSYM model. Fiber production would also be decreased when mean temperatures rise above 32 °C. Rise in temperature in future ultimately will enhance irrigation water demand by evaporating more water (Reddy et al., 2002). Hatfield et al. (2011) also reported that the expected temperature increase and variability in rainfall in the future could potentially offset the positive effect of increased CO_2 on cotton yield. Other studies of climate change by using different scenarios of A2, B2 and A1B revealed that there would 3.95, 3.20 and 1.85 °C increase in average temperature than baseline during cotton growing season in India and there would be 477 kg ha^{-1} and 268 kg ha^{-1} yield reduction for A2 and B2 scenarios respectively (Hebbar et al., 2013). Using three climatic models under A2 emission scenario and assuming CO_2 to be constant, Adhikari et al. (2015) reported that cotton yield would decrease (4 to 17%) due to rising temperatures during the 2041–2070 time span. They also stated that cotton yield will increase by 14–29% as compared with baseline yield in the Texas High Plains, USA by using RCM3-GFDL, RCM3-CCSM and RCM3-CGCM3. Similar results are also supported by Modala et al., 2015 they also assessed climate change impact on cotton production in the same region by using CSM-CROPGRO-Cotton model. By contrast, Voloudakis et al. (2015) in Greece predicted a decrease followed by an increase in cotton yield up to 2050 and the end of century respectively, due to a 1.8 °C and 4 °C increase in temperature, based on eight climatic models and IPCC's A1B emission scenario using the Aqua Crop model. These results do not differ much from those associated with one of the most widely used models (GOSSYM) tested in the south-central region of the USA. Reddy et al. (2005) used the outputs from a regional climate model as inputs in to GOSSYM to assess changes in cotton yields. They reported a 35% increase in seed cotton yield due to CO_2fertilization only and out of this 13% associated to other climatic variables.

4. Conclusions

Field experiments were conducted to calibrate and evaluate the CSM-CROPGRO-Cotton model under DSSAT v 4.6. The calibrated model was capable to simulate the studied parameters of different cultivars sown at various planting dates. The analysis of climate change scenarios of 29 GCMs and RCPs (4.4 and 8.5) indicates the less promising climatic conditions for cotton growth. Maximum consensus settled by the GCMs, revealed the increase in temperature of 1.2–1.8 °C and 2.2–3.1 °C in RCP 4.5 while 1.4–2.2 °C and 3.0–3.9 °C increase is expected under RCP 8.5 in near term and mid-century time periods, respectively. Similarly, rainfall changes are expected −8% to 15% and −5 to 17% in RCP 4.5 while −8 to 22% in near term and −2 to 20% in mid-century for RCP 8.5 scenario in near term and mid-century time periods, respectively. Furthermore, GISS-E2H, CMCC-CMS, CSIRO-MK3-6-0, GFDL-ESM2M and GFDL-ESM2G were found hotter in RCP 4.5 scenario while MIROC-ESM, CMCC-CMS, GFDL-ESM2M and GFDL-ESM2G were found much hotter in RCP 8.5 scenario. Generally, GCMs showed the trend toward increase in precipitation (wet conditions) under both scenarios of RCPs, while few GCMs were found the drier ones (GFDL-ESM2G, GFDL-ESM2M and IPSL-CM5A-LR in RCP 4.5 and CMCC-CM5 and MPI-ESM-MR in RCP 8.5). Mean ensemble results of GCMs reveal that cotton is expected to decrease in yield on average by 8% and 20% in near term and mid-century time spans respectively under RCP 4.5, due to climate change. Mean seed cotton yield would also decrease by 12% and 30% on average for all GCMs in near-term and mid-century respectively in RCP 8.5. Whereas the negative impact of climate change on cotton production is very uncertain, higher share of uncertainties is associated with the GCMs than emission scenarios (RCP 4.5 and RCP 8.5). GCMs, GFDL-ESM2M, GFDL-ESM2G and MIROC-ESM predicted a higher mean SCY reduction in RCP 4.5. Higher mean SCY reduction (16%–19%) is expected in RCP 8.5 by the GCMs, CMCC-CMS, IPSL-CM5B-LR, GISS-E2-H, GFDL-ESM2M and GFDL-ESM2G as compared with baseline yield (4147 kg ha^{-1}). Climate models like, CCSM4, HadGEM2-CC, HadGEM2-ES, INMCM4, CanESM2, CNRM-CM5, ACCESS1-0, BNU-ESM and MIROC5 are found less uncertain and showed stable behavior. Therefore, these models can be used for climate change impact assessment for other crops in the region. Adaptation management options like five weeks early sowing than current sowing date (10-May), increasing nitrogen fertilization (30%), split irrigation at critical growth stages, higher planting density (18% for spreading and 30% for erect type cultivars) and 17% increase in genetic potential of cultivars would compensate the negative impacts of climate change. This study provide valuable understandings and direction for cotton adaptation management options under climate change scenarios. Adaptation options like nitrogen fertilization and irrigation may include significant expenses and it will require additional feasibility about economics aspects and sustainability assessments. Future studies are desired to include the socio-economic impacts of the different adaptation management options.

Acknowledgements

The lead author is grateful to the Higher Education Commission (HEC) of Pakistan for providing financial support under International Research Support Initiative Program (IRSIP) to visit AgWeatherNet, Washington State University, Prosser, WA, USA. The first author is also thankful to Agricultural Model Inter-comparison and Improvement Project (AgMIP) for providing the technical and moral support for successful completion of this study. We also acknowledge the approach and methodology adopted in this study to categorize the GCMs into different classes (https://www.climatechangeinaustralia.gov.au/en/). Last but not least, lot of thanks go to all respected teachers and colleagues of Agro-Climatology Laboratory (Department of Agronomy,

University of Agriculture, Faisalabad-Pakistan), for their time to help during the research work.

References

Abbas, G., Ahmad, S., Ahmad, A., Nasim, W., Fatima, Z., Hussain, S., Rehman, M.H.U., Khan, M.A., Hasanuzzaman, M., Fahad, S., Boote, K.J., Hoogenboom, G., 2017. Quantification the impacts of climate change and crop management on phenology of maize-based cropping system in Punjab. Pak. Agric. For. Meteorol. 247, 42–55. http://dx.doi.org/10.1016/j.agrformet.2017.07.012.

Adhikari, P., Ale, S., Bordovsky, J.P., Thorp, K.R., Modala, N.R., Rajan, N., Barnes, E.M., 2015. Simulating future climate change impacts on seed cotton yield in the Texas high plains using the CSM-CROPGRO-cotton model. Agric. Water Manag. 164, 317–330. http://dx.doi.org/10.1016/j.agwat.2015.10.011.

AgMIP, 2013a. Guide for Running AgMIP Climate Scenario Generation Tools With R in Windows. AgMIP. http://www.agmip.org/wp-content/uploads/2013/10/Guide-for-Running-AgMIP-Climate-Scenario-Generation-with-R-v2.3.pdf.

AgMIP, 2013b. The coordinated climate-crop modeling project C3MP: an initiative of the agricultural model inter comparison and improvement project. C3MP Protocols and Procedures. AgMIP. http://research.agmip.org/download/attachments/1998899/C3MP+Protocols+v2.pdf.

AgMIP, 2014. Guide for Regional Integrated Assessments: Handbook of Methods and Procedures, Version 5.1. AgMIP. http://www.agmip.org/wpcontent/uploads/2013/06/AgMIPRegional%20Research-Team-Handbook-v4.2.pdf.

Ahmad, A., Ashfaq, M., Rasul, G., Wajid, S.A., Khaliq, T., Rasul, F., Saeed, U., Rahman, M.H., Hussain, J., Baig, I.A., Naqvi, S.A.A., Bokhari, S.A.A., Ahmad, S., Naseem, W., Hoogenboom, G., Valdivia, R., 2015. Impact of climate change on the rice–wheat cropping system of Pakistan. In: Rosenzweig, C., Hillel, D. (Eds.), Handbook of Climate Change and Agro Ecosystems: The Agricultural Model Inter Comparison and Improvement Project Integrated Crop and Economic Assessments, Part. 2. Imperial College Press, London.

Ahmad, S., Abbas, Q., Abbas, G., Fatima, Z., -ur-Rehman, Atique, Naz, S., Younis, H., Khan, R., Nasim, W., Habib Ur Rehman, M., Ahmad, A., Rasul, G., Khan, M., Hasanuzzaman, M., 2017. Quantification of climate warming and crop management impacts on cotton phenology. Plants 6, 7. http://dx.doi.org/10.3390/plants6010007.

Amin, A., Nasim, W., Mubeen, M., Ahmad, A., Nadeem, M., Urich, P., Fahad, S., Ahmad, S., Wajid, A., Tabassum, F., Hammad, H.M., Sultana, S.R., Anwar, S., Baloch, S.K., Wahid, A., Wilkerson, C.J., Hoogenboom, G., 2017a. Simulated CSM-CROPGRO-cotton yield under projected future climate by SimCLIM for southern Punjab. Pak. Agric. Syst. http://dx.doi.org/10.1016/j.agsy.2017.05.010.

Amin, A., Nasim, W., Mubeen, M., Kazmi, D.H., Lin, Z., Wahid, A., Sultana, S.R., Gibbs, J., Fahad, S., 2017b. Comparison of future and base precipitation anomalies by SimCLIM statistical projection through ensemble approach in Pakistan. Atmos. Res. 194, 214–225. http://dx.doi.org/10.1016/j.atmosres.2017.05.002.

Araya, A., Hoogenboom, G., Luedeling, E., Hadgu, K.M., Kisekka, I., Martorano, L.G., 2015. Assessment of maize growth and yield using crop models under present and future climate in Southwestern Ethiopia. Agric. For. Meteorol. 214–215, 252–265.

Asseng, S., 2013. Uncertainty in simulating wheat yields under climate change. Nat. Clim. Change 3, 627–632. http://dx.doi.org/10.1038/ncliamte1916.

Asseng, S., Ewert, F., Martre, P., Rötter, R.P., Lobell, D.B., Cammarano, D., Kimball, B.A., Ottman, M.J., Wall, G.W., White, J.W., Reynolds, M.P., Alderman, P.D., Prasad, P.V.V., Aggarwal, P.K., Anothai, J., Basso, B., Biernath, C., Challinor, A.J., De Sanctis, G., Doltra, J., Fereres, E., Garcia-Vila, M., Gayler, S., Hoogenboom, G., Hunt, L.A., Izaurralde, R.C., Jabloun, M., Jones, C.D., Kersebaum, K.C., Koehler, A.-K., Müller, C., Kumar, Naresh, Nendel, S., O'Leary, C., Olesen, G., Palosuo, T., Jørgen, E., Priesack, E., EyshiRezaei, E., Ruane, E., Semenov, A., Shcherbak, I., Mikhail, A., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Thorburn, P.J., Tao, F., Waha, E., Wang, E., Wallach, D., Wolf, J., Zhao, Z., Zhu, Y., 2014. Rising temperatures reduce global wheat production. Nat. Clim. Change 5, 143–147. http://dx.doi.org/10.1038/nclimate2470.

Awais, M., Wajid, A., Nasim, W., Ahmad, A., Saleem, M.F., Sammar Raza, M.A., Bashir, M.U., Habib-ur-Rahman, M., Saeed, U., Hussain, J., Arshad, N., Hoogenboom, G., 2017. Modeling the water and nitrogen productivity of sunflower using OILCROP-SUN model in Pakistan. Field Crops Res. 205, 67–77. http://dx.doi.org/10.1016/j.fcr.2017.01.013.

Bange, M.P., Milroy, S.P., 2004. Impact of short-term exposure to cold night temperatures on early development of cotton (Gossypiumhirsutum L.). Aust. J. Agric. Res. 55, 655–664.

Bassu, S., Brisson, N., Durand, J.L., Boote, K., Lizaso, J., Jones, J.W., Rosenzweig, C., Ruane, A.C., Adam, M., Baron, C., Basso, B., Biernath, C., Boogaard, H., Conijn, S., Corbeels, M., Deryng, D., De Sanctis, G., Gayler, S., Grassini, P., Hatfield, J., Hoek, S., Izaurralde, C., Jongschaap, R., Kemanian, A.R., Kersebaum, K.C., Kim, S.H., Kumar, N.S., Makowski, D., Müller, C., Nendel, C., Priesack, E., Pravia, M.V., Sau, F., Shcherbak, I., Tao, F., Teixeira, E., Timlin, D., Waha, K., 2014. How do various maize crop models vary in their responses to climate change factors? Glob. Change Biol. 20, 2301–2320. http://dx.doi.org/10.1111/gcb.12520.

Boote, K.J., Pickering, N.B., 1994. Modeling photosynthesis of row crop canopies. Hortic. Sci.

Challinor, A.J., Smith, M.S., Thornton, P., 2013. Use of agro-climate ensembles for quantifying uncertainty and informing adaptation. Agric. For. Meteorol. 170, 2–7. http://dx.doi.org/10.1016/j.agrformet.2012.09.007.

Cottee, N.S., Tan, D.K.Y., Bange, M.P., Cothren, J.T., Campbell, L.C., 2010. Multi-level determination of heat tolerance in cotton (Gossypiumhirsutum L.) under field conditions. Crop Sci. 50, 2553–2564.

Ewert, F., Rötter, R.P., Bindi, M., Webber, H., Trnka, M., Kersebaum, K.C., Olesen, J.E., van Ittersum, M.K., Janssen, S., Rivington, M., Semenov, M.A., Wallach, D., Porter, J.R., Stewart, D., erhagen, J., Gaiser, T., Palosuo, T., Tao, F., Nendel, C., Roggero, P.P., Bartošová, L., Asseng, S., 2015. Crop modelling for integrated assessment of risk to food production from climate change. Environ. Model. Softw. 72, 287–303. http://dx.doi.org/10.1016/j.envsoft.2014.12.003.

Fahad, S., Bano, A., 2012. Effect of salicylic acid on physiological and biochemical characterization of maize grown in saline area. Pak. J. Bot. 44, 1433–1438.

Fahad, S., Chen, Y., Saud, S., Wang, K., Xiong, D., Chen, C., Wu, C., Shah, F., Nie, L., Huang, J., 2013. Ultraviolet radiation effect on photosynthetic pigments, biochemical attributes, antioxidant enzyme activity and hormonal contents of wheat. J. Food Agric. Environ. 11 (3&4), 1635–1641.

Fahad, S., Hussain, S., Bano, A., Saud, S., Hassan, S., Shan, D., Khan, F.A., Khan, F., Chen, Y., Wu, C., Tabassum, M.A., Chun, M.X., Afzal, M., Jan, A., Jan, M.T., Huang, J., 2014a. Potential role of phytohormones and plant growth-promoting rhizobacteria in abiotic stresses: consequences for changing environment. Environ. Sci. Pollut. Res. http://dx.doi.org/10.1007/s11356-014-3754-2.

Fahad, S., Hussain, S., Matloob, A., Khan, F.A., Khaliq, A., Saud, S., Hassan, S., Shan, D., Khan, F., Ullah, N., Faiq, M., Khan, M.R., Tareen, A.K., Khan, A., Ullah, A., Ullah, N., Huang, J., 2014b. Phytohormones and plant responses to salinity stress: a review. Plant. Growth Regul. http://dx.doi.org/10.1007/s10725-014-0013-y.

Fahad, S., Hussain, S., Saud, S., Tanveer, M., Bajwa, A.A., Hassan, S., Shah, A.N., Ullah, A., Wu, C., Khan, F.A., Shah, F., Ullah, S., Chen, Y., Huang, J., 2015a. A biochar application protects rice pollen from high-temperature stress. Plant. Physiol. Biochem. 96, 281–287.

Fahad, S., Nie, L., Chen, Y., Wu, C., Xiong, D., Saud, S., Hongyan, L., Cui, K., Huang, J., 2015b. Crop plant hormones and environmental stress. Sustain. Agric. Rev. 15, 371–400.

Fahad, S., Hussain, S., Saud, S., Hassan, S., Chauhan, B.S., Khan, F., et al., 2016a. Responses of rapid viscoanalyzer profile and other rice grain qualities to exogenously applied plant growth regulators under high day and high night temperatures. PLoS One. 11 (7), e0159590. http://dx.doi.org/10.1371/journal.pone.0159590.

Fahad, S., Hussain, S., Saud, S., Khan, F., Hassan Jr, S., Amanullah, Nasim, W., Arif, M., Wang, F., Huang, J., 2016b. Exogenously applied plant growth regulators affect heat-stressed rice pollens. J. Agron. Crop. Sci. 202, 139–150.

Fahad, S., Hussain, S., Saud, S., Hassan, S., Ihsan, Z., Shah, A.N., Wu, C., Yousaf, M., Nasim, W., Alharby, H., Alghabari, F., Huang, J., 2016c. Exogenously applied plant growth regulators enhance the morpho physiological growth and yield of rice under high temperature. Front. Plant Sci. 7, 1250. http://dx.doi.org/10.3389/fpls.2016.01250.

Fahad, S., Hussain, S., Saud, S., Hassan, S., Tanveer, M., Ihsan, M.Z., Shah, A.N., Ullah, A., Nasrullah, K.F., Ullah, S., Alharby, H., Wu, C., Huang, J., 2016d. A combined application of biochar and phosphorus alleviates heat-induced adversities on physiological, agronomical and quality attributes of rice. Plant. Physiol. Biochem. 103, 191–198.

GOP, 2015. Economic Survey of Pakistan 2014-15. Ministry of Food, Agriculture and Livestock, Economic Wing, Islamabad, Pakistan, pp. 20–21.

Gwimbi, P., Mundoga, T., 2010. Impact of climate change on cotton production under rainfed conditions: case of Gokwe. J. Sustain. Dev. Afr. 12, 59–69.

Hatfield, J.L., Boote, K.J., Kimball, B.A., Ziska, L.H., Izaurralde, R.C., Ort, D., Thomson, A.M., Wolfe, D., 2011. Climate impacts on agriculture: implications for crop production. Agron. J. 103, 351–370. http://dx.doi.org/10.2134/agronj2010.0303.

Hatfield, J.L., Prueger, J.H., 2015. Temperature extremes: effect on plant growth and development. Weather Clim. Extremes 10, 4–10. http://dx.doi.org/10.1016/j.wace.2015.08.001.

Hebbar, K.B., Venugopalan, M.V., Prakash, A.H., Aggarwal, P.K., 2013. Simulating the impacts of climate change on cotton production in India. Clim. Change 118, 701–713. http://dx.doi.org/10.1007/s10584-012-06734.

Hoogenboom, G., Jones, J.W., Wilkens, P.W., Porter, C.H., Boote, K.J., Hunt, L.A., Singh, U., Lizaso, J.L., White, J.W., Uryasev, O., Royce, F.S., Ogoshi, R., Gijsman, A.J., Tsuji, G.Y., 2010. Decision Support System for Agro Technology Transfer Version 4.5. [CD-ROM]. University of Hawaii, Honolulu.

Hoogenboom, G., Jones, J.W., Wilkens, P.W., Porter, C.H., Boote, K.J., Hunt, L.A., Singh, U., Lizaso, J.I., White, J.W., Uryasev, O., Ogoshi, R., Koo, J., Shelia, V., Tsuji, G.Y., 2015. Decision Support System for Agro Technology Transfer (Dssat) Version 4.6. DSSAT Foundation, Prosser, Washington. http://dssat.net.

Hunt, L.A., Boote, K.J., 1998. Data for model operation, calibration, and evaluation. In: Tsuji, G.Y., Hoogenboom, G., Thornton, P.K. (Eds.), Understanding Options for Agricultural Production. Systems Approaches for Sustainable Agricultural Development. Kluwer Academic, Dordrecht.

IPCC, 2013. Summary for policymakers, in: climate change 2013. The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. pp. 33. http://dx.doi.org/10.1017/CBO9781107415324.

IPCC, 2014. Climate Change 2014 Synthesis Report Summary Chapter for Policymakers 31 IPCChttp://dx.doi.org/10.1017/CBO9781107415324.

Iqbal, M.A., Ping, Q., Abid, M., Muhammad Muslim Kazmi, S., Rizwan, M., 2016. Assessing risk perceptions and attitude among cotton farmers: A case of Punjab province. Pak. Int. J. Disaster Risk Reduct. 16, 68–74. http://dx.doi.org/10.1016/j.ijdrr.2016.01.009.

Iqbal, 2011. Modeling the Impact of Climate Change on Seed Cotton (Gossypiumhirsutum L.) Yield in Punjab Pakistan. Ph.D Thesis. Dept. of Agron; Univ. of Agric., Faisalabad.

Jamieson, P.D., Porter, J.R., Wilson, D.R., 1991. A test of the computer simulation model ARCWHEAT1 on wheat crops grown in New Zealand. Field Crops Res. 27, 337–350. http://dx.doi.org/10.1016/0378-4290(91)90040-3.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A.,

Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping system model. Eur. J. Agron. http://dx.doi.org/10.1016/S1161-0301(02)00107-7.
Kassie, B.T., Asseng, S., Rotter, R.P., Hengsdijk, H., Ruane, A.C., Van Ittersum, M.K., 2015. Exploring climate change impacts and adaptation options for maize production in the Central Rift Valley of Ethiopia using different climate change scenarios and crop models. Clim. Change 129, 145–158. http://dx.doi.org/10.1007/s10584-014-1322-x.
Kersebaum, K.C., Boote, K.J., Jorgenson, J.S., Nendel, C., Bindi, M., Frühauf, C., Gaiser, T., Hoogenboom, G., Kollas, C., Olesen, J.E., Rötter, R.P., Ruget, F., Thorburn, P.J., Trnka, M., Wegehenkel, M., 2015. Analysis and classification of data sets for calibration and validation of agro-ecosystem models. Environ. Model. Softw. 72, 402–417. http://dx.doi.org/10.1016/j.envsoft.2015.05.009.
Kimball, B.A., Zhu, J., Cheng, L., Kobayashi, K., Bindi, M., 2002. Responses of agricultural crops of free-air CO2 enrichment. Ying Yong Sheng Tai Xue Bao 13, 1323–1338.
Kiniry, J.R., Williams, J.R., Vanderlip, R.L., Atwood, J.D., Reicosky, D.C., Mulliken, J., Cox, W.J., Mascagni, H.J., Hollinger, S.E., Wiebold, W.J., 1997. Evaluation of two maize models for nine U.S. locations. Agron. J. 89, 421–426.
Loague, K., Green, R.E., 1991. Statistical and graphical methods for evaluating solute transport models: overview and application. J. Contam. Hydrol. 7, 51–73. http://dx.doi.org/10.1016/0169-7722(91)90038-3.
Luo, Q., 2011. Temperature thresholds and crop production: a review. Clim. Change 109, 583–598. http://dx.doi.org/10.1007/s10584-011-0028-6.
Luo, Q., Bange, M., Braunack, M., Johnston, D., 2016. Effectiveness of agronomic practices in dealing with climate change impacts in the Australian cotton industry–a simulation study. Agric. Syst. 147, 1–9. http://dx.doi.org/10.1016/j.agsy.2016.05.006.
Luo, Q., Bange, M., Clancy, L., 2014. Cotton crop phenology in a new temperature regime. Ecol. Model. 285, 22–29. http://dx.doi.org/10.1016/j.ecolmodel.2014.04.018.
Mason-D'Croz, D., Vervoort, J., Palazzo, A., Islam, S., Lord, S., Helfgott, A., Havlík, P., Peou, R., Sassen, M., Veeger, M., van Soesbergen, A., Arnell, A.P., Stuch, B., Arslan, A., Lipper, L., 2016. Multi-factor, multi-state, multi-model scenarios: exploring food and climate futures for Southeast Asia. Environ. Model. Softw. 83, 255–270. http://dx.doi.org/10.1016/j.envsoft.2016.05.008.
Meehl, G.A., Covey, C., Delworth, T., Latif, M., McAvaney, B., Mitchell, J.F.B., Stouffer, R.J., Taylor, K.E., 2007. The WCRP CMIP3 multimodel dataset: a new era in climatic change research. Bull. Am. Meteorol. Soc. 88, 1383–1394. http://dx.doi.org/10.1175/BAMS-88-9-1383.
Modala, N.R., Ale, S., Rajan, N., Munster, C.L., DeLaune, P.B., Thorp, K.R., Nair, S.S., Barnes, E.M., 2015. Evaluation of the CSM-CROPGRO-cotton model for the Texas rolling plains region and simulation of deficit irrigation strategies for increasing water use efficiency. Trans. ASABE 58, 685–696. http://dx.doi.org/10.13031/trans.58.10833.
Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., van Vuuren, D.P., Carter, T.R., Emori, S., Kainuma, M., Kram, T., Meehl, G.A., Mitchell, J.F.B., Nakicenovic, N., Riahi, K., Smith, S.J., Stouffer, R.J., Thomson, A.M., Weyant, J.P., Wilbanks, T.J., 2010. The next generation of scenarios for climate change research and assessment. Nature 463, 747–756.
Nasim, W., Ahmad, A., Belhouchette, H., Fahad, S., Hoogenboom, G., 2016c. Evaluation of the OILCROP-SUN model for sunflower hybrids under different agro-meteorological conditions of Punjab-Pakistan. Field Crops Res. 188, 17–30.
Nasim, W., Ahmad, A., Hammad, H.M., Chaudhary, H.J., Munis, M.F.H., 2012. Effect of nitrogen on growth and yield of sunflower under semiarid conditions of Pakistan. Pak. J. Bot. 44 (2), 639–648.
Nasim, W., Ahmad, A., Wajid, A., Akhtar, J., Muhammad, D., 2011. Nitrogen effects on growth and development of sunflower hybrids under agro-climatic conditions of Multan. Pak. J. Bot. 43 (4), 2083–2092.
Nasim, W., Belhouchette, H., Ahmad, A., Rahman, M.H., Jabran, K., Ullah, K., Fahad, S., Shakeel, M., Hoogenboom, G., 2016b. Modelling climate change impacts and adaptation strategies for sunflower in Punjab-Pakistan. Outlook Agric. 45 (1), 39–45.
Nasim, W., Belhouchette, H., Tariq, M., Fahad, S., et al., 2016a. Correlation studies on nitrogen for sunflower crop across the agroclimatic variability. Environ. Sci. Pollut. Res. 23 (4), 3658–3670.
Nasim, W., Belhouchette, H., Ahmad, A., Habib-ur-Rahman, M., Jabran, K., Ullah, K., Fahad, S., Shakeel, M., Hoogenboom, G., 2016. Modelling climate change impacts and adaptation strategies for sunflower in Pakistan. Outlook Agric. 45, 39–45.
Ortiz, B.V., Hoogenboom, G., Vellidis, G., Boote, K., Davis, R.F., Perry, C., 2009. Adapting the CROPGRO-cotton model to simulate cotton biomass and yield under southern root-knot nematode parasitism. Trans. ASAE 52, 2129–2140.
Osborne, T., Rose, G., Wheeler, T., 2013. Variation in the global-scale impacts of climate change on crop productivity due to climate model uncertainty and adaptation. Agric. For. Meteorol. 170, 183–194.
Pathak, T.B., Fraisse, C.W., Jones, J.W., Messina, C.D., Hoogenboom, G., 2007. Use of global sensitivity analysis for CROPGRO cotton model development. Trans. ASABE 50, 2295–2302.
Paz, J.O., Woli, P., Garcia y Garcia, A., Hoogenboom, G., 2012. Cotton yields as influenced by ENSO at different planting dates and spatial aggregation levels. Agric. Syst. 111, 45–52.
Rahman, M.H., Ahmad, A., Wajid, A., Hussain, M., Akhtar, J., Hoogenboom, G., 2016. Estimation of temporal variation resilience in cotton varieties using statistical models. Pak. J. Agri. Sci. 53, 169–186.
Rahman, M.H.U., Ahmad, A., Wajid, A., Hussain, M., Rasul, F., Ishaque, W., Islam, M.A., Shelia, V., Awais, M., Ullah, A., Wahid, A., Sultana, S.R., Saud, S., Khan, S., Fahad, S., Hussain, M., Hussain, S., Nasim, W., 2017. Application of CSM-CROPGRO-cotton model for cultivars and optimum planting dates: evaluation in changing semi-arid climate. F. Crop. Res. 0–1. http://dx.doi.org/10.1016/j.fcr.2017.07.007.
Reddy, K.R., Doma, P.R., Mearns, L.O., Boone, M.Y.L., Hodges, H.F., Richardson, A.G., Kakani, V.G., 2002. Simulating the impacts of climate change on cotton production in the Mississippi delta. Clim. Res. 22, 271–281. http://dx.doi.org/10.3354/cr022271.
Reddy, K.R., Koti, S., Davidonis, G.H., Reddy, V.R., 2004. Interactive effects of carbon dioxide and nitrogen nutrition on cotton growth, development, yield, and fiber quality. Agronomy 96, 1148–1157.
Reddy, K.R., Vara Prasad, P.V., Kakani, V.G., 2005. Crop responses to elevated carbon dioxide and interactions with temperature. J. Crop Improv. 13, 157–191. http://dx.doi.org/10.1300/J411v13n01_08.
Reddy, K.R., Zhao, D., 2005. Interactive effects of elevated CO2 and potassium deficiency on photosynthesis, growth, and biomass partitioning of cotton. Field Crops Res. 94, 201–213.
Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C., Müller, C., Arneth, A., Boote, K.J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T., a, M., Schmid, E., Stehfest, E., Yang, H., Jones, J.W., 2014. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model inter comparison. Proc. Natl. Acad. Sci. U. S. A. 111, 3268–3273.
Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., Nelson, G.C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., Winter, J.M., 2013. The agricultural model inter comparison and improvement project (AgMIP): protocols and pilot studies. Agric. For. Meteorol. 170, 166–182. http://dx.doi.org/10.1016/j.agrformet.2012.09.011.
Rötter, R.P., Carter, T.R., Olesen, J.E., Porter, J.R., 2011. Crop–climate models need an overhaul. Nat. Clim. Change 1, 175–177. http://dx.doi.org/10.1038/nclimate1152.
Ruane, A.C., Cecil, L.D., Horton, R.M., Gordón, R., McCollum, R., Brown, D., Killough, B., Goldberg, R., Greeley, A.P., Rosenzweig, C., 2013. Climate change impact uncertainties for maize in Panama: farm information, climate projections, and yield sensitivities. Agric. For. Meteorol. 170, 132–145.
Ruane, A.C., Goldberg, R., Chryssanthacopoulos, J., 2015a. Climate forcing datasets for agricultural modeling: merged products for gap-filling and historical climate series estimation. Agric. For. Meteorol. 200, 233–248. http://dx.doi.org/10.1016/j.agrformet.2014.09.016.
Ruane, A.C., Winter, J.M., McDermid, S.P., Hudson, N.I., 2015b. AgMIP climate datasets and scenarios for integrated assessment. in handbook of climate change and agroecosystems: the agricultural model inter comparison and improvement project (AgMIP) integrated crop and economic assessments, part 1. In: In: Rosenzweig, C., Hillel, D. (Eds.), ICP Series on Climate Change Impacts, Adaptation, and Mitigation, vol. 3. Imperial College Press, pp. 45–78. http://dx.doi.org/10.1142/9781783265640_0003.
Rasul, F., Gull, U., Habib Ur Rahman, M., Hussain, Q., Chaudhary, H.J., Matloob, A., Shahzad, S., Iqbal, S., Shelia, V., Masood, S., Bajwa, H.M., 2016. Biochar: an emerging technology for climate change mitigation. J. Environ. Agric. Sci. 9, 37–43.
Schlenker, W., Roberts, M.J., 2009. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. Proc. Natl. Acad. Sci. 106, 15594–15598.
Singh, R.P., Prasad, P.V.V., Sunita, K., Giri, S.N., Reddy, K.R., 2007. Influence of high temperature and breeding for heat tolerance in cotton: a review. Adv. Agron. 313–385.
Soler, C.M.T., Sentelhas, P.C., Hoogenboom, G., 2007. Application of the CSM-CERES-maize model for planting date evaluation and yield forecasting for maize grown off-season in a subtropical environment. Eur. J. Agron. 27, 165–177. http://dx.doi.org/10.1016/j.eja.2007.03.002.
Tao, F., Yokozawa, M., Zhang, Z., 2009. Modelling the impacts of weather and climate variability on crop productivity over a large area: a new process-based model development, optimization, and uncertainties analysis. Agric. For. Meteorol. 149, 831–850. http://dx.doi.org/10.1016/j.agrformet.2008.11.004.
Tebaldi, C., Knutti, R., 2007. The use of the multi-model ensemble in probabilistic climate projections. Philos. Trans. R. Soc. A Math. Phys. Eng. Sci. 365, 2053–2075. http://dx.doi.org/10.1098/rsta.2007.2076.
Thorp, K.R., Ale, S., Bange, M.P., Barnes, E.M., Hoogenboom, G., Lascano, R.J., McCarthy, A.C., Nair, S., Paz, J.O., Rajan, N., Reddy, K.R., Wall, G.W., White, J.W., 2014. Development and application of process-based simulation models for cotton production: a review of past, present, and future directions. J. Cotton Sci. 18, 10–47.
Uusitalo, L., Lehikoinen, A., Helle, I., Myrberg, K., 2015. An overview of methods to evaluate uncertainty of deterministic models in decision support. Environ. Model. Softw. 63, 24–31. http://dx.doi.org/10.1016/j.envsoft.2014.09.017.
Van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G.C., Kram, T., Krey, V., Lamarque, J.F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S.J., Rose, S.K., 2011. The representative concentration pathways: an overview. Clim. Change 109, 5–31.
Voloudakis, D., Karamanos, A., Economou, G., Kalivas, D., Vahamidis, P., Kotoulas, V., Kapsomenakis, J., Zerefos, C., 2015. Prediction of climate change impacts on cotton yields in Greece under eight climatic models using the AquaCrop crop simulation model and discriminant function analysis. Agric. Water Manag. 147, 116–128. http://dx.doi.org/10.1016/j.agwat.2014.07.028.
Wajid, A., Rahman, M.H.U., Ahmad, A., Khaliq, T., Mahmood, N., Rasul, F., Bashir, M.U., Awais, M., Hussain, J., Hoogeboom, G., 2013. Simulating the interactive impact of nitrogen and promising cultivars on yield of lentil (Lens culinaris) using CROPGRO-legume model. Int. J. Agric. Biol. 15, 1331–1336. http://dx.doi.org/10.13140/RG.2.1.1430.4168.
Wajid, A., Ahmad, A., Hussain, M., Rahman, M.H.U., Khaliq, T., Mubeen, M., Rasul, F., Bashir, U., Awais, M., Iqbal, J., Sultana, S.R., Hoogenboom, G., 2014. Modeling growth, development and seed-cotton yield for varying nitrogen increments and planting dates using DSSAT. Pak. J. Agric. Sci. 51, 641–650.
Wallach, D., Goffinet, B., 1989. Mean squared error of prediction as a criterion for evaluating and comparing system models. Ecol. Model. 44 (3–4), 299–306.
White, J.W., Hoogenboom, G., Kimball, B.A., Wall, G.W., 2011. Methodologies for

simulating impacts of climate change on crop production. Field Crops Res. 124, 357–368. http://dx.doi.org/10.1016/j.fcr.2011.07.001.
Whitfield, S., 2013. Uncertainty, ignorance and ambiguity in crop modelling for African agricultural adaptation. Clim. Change 120, 325–340. http://dx.doi.org/10.1007/s10584-013-0795-3.
Wilby, R.L., Charles, S.P., Zorita, E., Timbal, B., Whetton, P., Mearns, L.O., 2004. Guidelines for use of climate scenarios developed from statistical downscaling methods. Analysis 27, 1–27 citeulike-article-id:8861447.
Wilby, R.L., Troni, J., Biot, Y., Tedd, L., Hewitson, B.C., Smith, D.M., Sutton, R.T., 2009. A review of climate risk information for adaptation and development planning. Int. J. Climatol. http://dx.doi.org/10.1002/joc.1839.
Wilks, D.S., 2011. Statistical Methods in the Atmospheric Sciences, third ed. Elsevier Publishers, New York0127519661 9780127519661.
Williams, A., White, N., Mushtaq, S., Cockfield, G., Power, B., Kouadio, L., 2015. Quantifying the response of cotton production in Eastern Australia to climate change. Clim. Change 129, 183–196. http://dx.doi.org/10.1007/s10584-014-1305-y.
Willmott, C.J., 1982. Some comments on the evaluation of model performance. Bull. Am. Meteorol. Soc. 63 (11), 1309–1313.
Willmott, C.J., Ackleson, S.G., Davis, R.E., Feddema, J.J., Klink, K.M., Legates, D.R., O'Donnell, J., Rowe, C.M., 1985. Statistics for the evaluation and comparison of models. J. Geophys. Res. Oceans 90, 8995–9005. http://dx.doi.org/10.1029/JC090iC05p08995.
Yang, Y., Yang, Y., Han, S., Macadam, I., Liu, D.L., 2014. Prediction of cotton yield and water demand under climate change and future adaptation measures. Agric. Water Manag. 144, 42–53.
Zamora, D.S., Jose, S., Jones, J.W., Cropper, W.P., 2009. Modeling cotton production response to shading in a pecan alley cropping system using CROPGRO. Agrofor. Syst. 76, 423–435.